THREE ESSAYS ON CLIMATE CHANGE, PINE BEETLE RISK, FOREST PRODUCTIVITY AND FORESTLAND VALUE

A Dissertation

by

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ABSTRACT

U.S. Forests are under significant pressure from global climate change. This study investigates the impact of climate change on U.S. forest at various aspects. In the first essay, I use a generalized linear model to examine how climatic conditions have influenced southern pine beetle (SPB; *Dendroctonus frontalis Zimmermann*) outbreaks in the southern U.S. and project future SPB infestations using the future climates projected by Global Climate models (GCMs). The estimation results indicate that climate significantly affects SPB outbreaks, but projected future SPB infestation would not move in one direction under the complex interactions between temperature and precipitation and the magnitude of damages would vary across the region. In the second essay, I use panel data analysis with various climate and spatial characteristic variables to investigate the effects of CO_2 fertilization and climate variables on forest productivity across the U.S. The results from the second essay indicate that there is a significant correlation between climate variables and forest productivity. Also, projected global climate change would enhance future forest productivity in the South, the Pacific Coastal, and the northern Great Plains of the U.S. but likely threaten forest productivity in some regions such as the southern Great Plains. In the third essay, I investigate how forest carbon credits and SPB risk associated with climate change affect individual landowner's decision making using a real options framework. The results of the third essay reveal that carbon sequestration would increase the value of standing forests, whereas higher SPB risk associated with climate change would reduce the forest value.

The higher value of standing forests would encourage the landowners to delay timber harvest. Overall results of this study show that climate change will have a mixed impact on U.S. forests, which requires region-specific adaptation and mitigation strategies.

DEDICATION

To my beloved family

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1. INTRODUCTION

The southern U.S. is one of the most productive forest regions in the world, supplying almost 60% of the timber in the U.S. and over 14% of industrial round wood in the world. Forest owners, however, are facing many uncertainties such as timber price volatility, unexpected climate events, and other disturbances. Moreover, ongoing climate change will enhance uncertainties including changes in average temperature and precipitation, and increases in occurrences of droughts and flooding. Ample evidence shows that climate change is proceeding and one of the crucial causes of climate changes is human-caused greenhouse gases emissions (IPCC 2007). From 1990 to 2012, the worldwide net greenhouse gases emission from human activities have been increased by 35% (US EPA 2015). Emissions of carbon dioxide (CO_2) which accounts for about three-fourths of total greenhouse gas emissions have been increased by 42% in the same period (US EPA 2015). An increasing concentration of greenhouse gases in the atmosphere is considered a major cause of global warming. The Intergovernmental Panel on Climate Change (IPCC) suggests increase in world average temperature range in size from 0.2–5.5°C by 2100 in their fifth assessment report (IPCC 2013). The rapid growth of greenhouse gases will be expected to change the earth's climate, temperature, precipitation, and temperature variability (IPCC 2013). Forests have a close relationship with climate factors such as temperature and precipitation. As climate change progresses, the uncertainties that forest owners are going to face are intensified because climate change is largely related to forest productivity and insect outbreaks that could

directly affect forest owner's profit.

The purpose of this dissertation is to examine issues which are related to understanding the impacts of climate change on forests in the U.S. at different aspects. The first and third essays focus on the southern U.S. In the second essay, the target area will be extended to all of the U.S. continental states. The specific objectives are:

- Investigate the relationship between climate factors and southern pine beetle (SPB) (Dendroctonus frontalis Zimmermann) risk and predict future SPB outbreak risks using projected future climate data;
- Investigate climate change effects on forest productivity using historical data and predict future forest productivity in the U.S. under future climate scenarios; and
- Examine optimal rotation age and forest bareland value under timber price volatility coupled with the value of forest carbon sequestration and SPB outbreak risk in the southern U.S.

In the first essay, I examine the effects of various climate variables including temperature, temperature extremes, and precipitation on SPB outbreak risk and project SPB infestations under future climate change. SPB infestations have been largely related to climate conditions, and ongoing global climate change is expected to alter the pattern of SPB infestation risk. The Generalized Linear Model (GLM) approach provides appropriate framework for investigating the relationship between various independent variables and SPB risk through control fractional dependent variables. In the projection part, I investigate the responses of SPB infestation under various climate change

scenarios. Also, expected future cyclical pattern and amplitude of SPB infestation are examined using cyclical pattern analysis.

The relationships between climate factors and forest productivity are examined in the second essay. Forest productivity is closely related to not only temperature and precipitation, but also other factors including soil quality, forest type, and tree density in the area. In addition, CO_2 concentration in the atmosphere plays a pivotal role in tree growth. To investigate the relationship between various dependent variables and forest productivity, panel data approach is used. Also, the future climate change impact on forest productivity is provided across multiple global climate scenarios. In the projection part, I consider changes of CO_2 concentration pathways in climate scenarios. This explores the potential future CO_2 impact on forest productivity.

In the third essay, I apply a suitable technique for valuing forestland and determining optimal harvest/rotation age. The most widely used static discount cash flow (DCF) method fails to include flexibility in forest harvesting decision. To overcome this weakness, a real option analysis is used to evaluate forestland value and optimal harvest decision under uncertainties. The main objective is to find optimal harvest age and forest bareland value considering timber price volatility, carbon sequestration ability of the forest, and SPB risk by applying real option to forest management problems.

The overall structure of the dissertation takes the form of five sections and appendix. Section 1 is a general introduction of the dissertation. Section 2 includes the first essay that is concerned with climate variability and SPB infestation. The relationship between climate variables and SPB risk, projected future SPB risk using

global climate models (GCMs), and hidden cyclical pattern in SPB outbreaks are reported in the second section. Section 3 is the second essay that examines the impact of climate variables on the forest productivity and project future climate change impact on forest productivity across the continental U.S. states under multiple global climate scenarios. Section 4 includes the third essay. In the third essay, I evaluate the changes in optimal harvest decision, forest bareland value, and harvest threshold ages using real option approach under various risks including timber price volatility, carbon sequestration ability of forest and tree damages by SPB infestation. Section 5 presents findings of the studies and overall conclusions.

2. CLIMATE VARIABILITY, ADAPTATION, AND SOUTHERN PINE BEETLE INFESTATION

Infestations of the southern pine beetle (SPB; *Dendroctonus frontalis Zimmermann*) are a major disturbance to pine forest ecosystems in the southern U.S. (Preisler et al. 2012). This region is one of the most productive forest regions in the U.S., supplying almost 60% of timber in the U.S. and over 14% of industrial round wood in the world (Smith et al. 2009). SPB outbreaks not only cause timber loss but also affect the structure and health of the forest ecosystem, increasing fire hazards and reducing forest carbon storage (Safranyik, Shrimpton, and Whitney 1975). SPB infestations have been found to be responsive to climatic conditions and are predicted to rise under climate change (Gan 2004). Previous works (Lorio and Hodges 1977; Safranyik et al. 2010; Raffa and Berryman 1982) on SPB infestation primarily have focused on two aspects: 1) explaining the factors that contribute to SPB population dynamics from entomological perspectives; and 2) modeling the relationship between SPB infestations and contributing factors using statistical tools and observed data.

Considerable work has been done in entomology to identify and explain the factors and their contribution to SPB outbreaks. Many factors have been found to be attributable to SPB infestations, including forest stand age (tree diameter), stand density, nearby beetle sources, host tree vigor, soil condition, environmental stress, water deficit, climatic conditions, along with other factors (Lorio and Hodges 1977). Among these factors, climate, however, is probably the most significant (Bentz et al. 2010; Carroll et

al. 2003). Climate conditions directly affect the dynamic of the SPB population and influence the health of host trees and natural predators of the SPB (Preisler et al. 2012). Moreover, ongoing global climate change accelerates the risk of SPB infestation because it increases the beetle population and distribution in the forest because of changes in average temperature and precipitation (Ungerer, Ayres, and Lombardero 1999).

Based on the Intergovernmental Panel on Climate Change (IPCC) report, projected average global temperature will increase by 2–4 °C by end of the twenty-first century under several emission scenarios (IPCC 2007), and such climate changes can cause potential movement of epidemic insect populations (Logan, Bentz, and Powell 2001). Changes in temperature likely have direct impacts on the beetle population dynamics while water shortage may have indirect impacts on the beetle through impacts on the host trees (Bentz et al. 2010).

One of the most significant temperature-related factors in SPB population dynamics is insect mortality resulting from cold exposure (Bentz et al. 2010). The stage of beetle development, durations of exposure to cold temperatures, responses to seasonal changes in temperature, and geographical locations influence the population of pine beetles. The SPB has four life stages: egg, larva, pupa, and adult. The third and fourth stages are usually exposed to the coldest weather from December to February (Bentz and Mullins 1999). Winter temperatures, therefore, are critical because frequent occurrences of severe winter temperatures decrease the survival of the immature and can cause widespread beetle mortality. SPB accumulates cryoprotectant such as glycerol compounds as temperature decreases during the fall (Bentz and Mullins 1999).

Increasing temperature associated with climate change, particularly in the fall during the periods of glycerol synthesis, induces beetle mortality (Bentz et al. 2010). Beetles increasingly develop cold tolerance with the decrease in fall temperatures, but abnormally cold weather increases the mortality rate (Régnière and Bentz 2007). In particular, dramatic temperature drops in fall and spring can result in death of many individuals (Gibbons, Hedeker, and DuToit 2010). These entomological studies have provided a theoretical basis for modeling.

Climate can also influence beetle infestations through its effect on host tree vigor and food abundance to the insects. Climate water stress may have a significant effect on host trees as well. Trees that face water stress are more easily exposed to beetle attacks because of lower resin production during the drought season (Bentz et al. 2010). If the beetle population has settled in stressed trees, even healthy trees in the neighboring area can be attacked by beetles (Gaylord 2014). Therefore, fast management action may be important to reduce the damage by beetle attacks. Recent large-scale outbreaks of mountain pine beetles in the western U.S. and Canada also suggest the vulnerability of the pine forests in the U.S. to bark beetles because climate change has altered structure and composition of forest in these areas (Negron and Fettig 2014). In this essay, I quantify the relationship between SPB infestations and climatic conditions in the southern U.S. and predict future SPB risk under predicted climate change in the region.

The specific steps for this essay are; 1) to investigate the relationship between climate factors and southern pine beetle (SPB) risk using the Generalized Linear Model (GLM); 2) to identify cyclical patterns of SPB outbreaks using cyclical pattern analysis;

and 3) to project future SPB risk using the future climate conditions projected by Global Climate Models (GCMs) to assess global climate change impact on SPB outbreak risk.

Several studies have employed statistical tools to estimate the relationship between SPB infestations and their contribution factors, in general, and climatic conditions, in particular. This study advances the previous modeling work in several aspects. First, I use generalized linear model to estimate the relationship between climatic conditions and SPB infestations, which can better handle the fractional dependent variable by ensuring that it remains within the range of [0, 1]. Second, I explore the potential impact of climate extremes (e.g., maximum and minimum seasonal temperatures), in addition to average seasonal temperatures and total seasonal precipitation, on SPB outbreaks, as these extremes have shown influences on SPB populations. Third, I incorporate independent variables representing forest conditions such as unsalvaged volume of infested trees into the model. The unsalvaged volume of infested trees could affect SPB infestations in the neighboring area. Also, the values of the variables can be altered by changing forest management practices. Thus, the variable may prove implications for adopting strategy to alleviate SPB damage by salvaging infested trees in the future.

In addition, the newly developed Representative Concentration Pathways (RCPs) climate scenarios based on the IPCC fifth assessment report (AR5) are adopted to project future SPB risks. The climate scenarios are used to ensure that projections are consistent across the various branches of climate science (Wayne 2013). The new set of scenarios for climate change is necessary to take into account scientific advances in the understanding of the climate system, as well as to include updated data on current and

historical emissions, climate change mitigation, and adaptation impact (Moss et al. 2010). Using the integrated RCP scenarios, I provide more robust estimates and projections of the SPB risks than previously found in the studies using the scenarios in SRES (IPCC 2000a).

2.1 Estimation method

2.1.1 Generalized linear model with fractional response variables

A traditional linear regression of $E(y|x)$ given X takes the following form:

$$E(y|x) = \beta_1 x_1 + \beta_2 x_2 + ...\beta_k x_k = X\beta \,. \tag{1}$$

where $X \equiv (x_1, x_2, ..., x_k)$ is a $1 \times K$ vector of explanatory variables with $x_1 \equiv 1$; y is the dependent variable; and β is a $K \times 1$ vector of coefficients to be estimated. Suppose a response variable, y, is fractional and bounded between 0 and 1. In this case, the linear modeling approach is inappropriate, and the estimation result could be biased because for certain values of x, the estimated $\hat{y}$ could be greater than one or less than zero, i.e., $\hat{y} > 1$ or $\hat{y} < 0$ (Papke and Wooldridge 1996). To overcome this problem, I employ the Generalized Linear Models (GLM) framework which can better treat the fractional response variable than a linear model for the log-odd ratio. A linear model for log-odd ratio is $E(\log[y/(1-y)]|x) = X\beta$. However, the equation cannot be defined if y has values 0 or 1 with positive probability so adjustments should be made before computing log-odds ratio if any observation y_i takes values 0 or 1 in a given data set (Papke and

Wooldridge 1996). The logit or probit link function in GLM ensures that the y value remains within the range of [0, 1], and the GLM framework allows the outcomes at the end points to be zero and one. Under the GLM, the link between the expected value of response and explanatory variables is

$$g(E[y|x]) = \beta_1 + \beta_2 x_2 + ...\beta_k x_k = X\beta, \quad (2)$$

where X, a $1 \times K$ vector, is a set of explanatory variables and $g(\cdot)$ is called a link function. Equation (2) linearly links the expected value of response variable y to the explanatory variables (Madsen and Thyregod 2011). To identify the model, we need to specify a distribution of the response variable y, explanatory variables, and the link function. The response variable follows a Bernoulli distribution in the GLM model. The link function $g(\cdot)$ is a smooth monotonic function. In this study, the inverse standard normal cumulative density function (CDF), $g(z) = \Phi^{-1}(z)$ is used as the link function (probit link function). Empirically, applying the logit or probit link function in binomial data generates similar estimation results (Hardin and Hilbe 2007), but probit is computationally simpler when we have unobserved heterogeneity or endogenous explanatory variables (Papke and Wooldridge 2008). Also, probit is preferred when researchers focus more on prediction rather than on parameter estimations (Hardin and Hilbe 2007). Because the link function, $g(z)$, satisfies $0 \le g(z) \le 1$ for all $z \in \mathbb{R}$, the value of y lies in the interval (0, 1). Also it is easy to recover the regression function using an inverse link function such that $\mu = g^{-1}(X\beta + \varepsilon) = E(y_{it}|x_{it})$. This is another

advantage of GLM compared to traditional logistic transformation (Hardin and Hilbe 2007).

2.1.2 Data and the empirical model

The empirical model for estimating the relationship between SPB risk and climate and forestry variables is

(3)
$$
\begin{aligned}
E[RISK_{it} \mid X_{it}] = \Phi\{\sum_{\rho=0}^{m} (\beta_0 &+ \beta_{1\rho} USV_{i,t-\rho} + \beta_{2\rho} SPT_{i,t-\rho} + \beta_{3\rho} SMT_{i,t-\rho} + \\
&+ \beta_{4\rho} FLT_{i,t-\rho} + \beta_{5\rho} WNT_{i,t-\rho} + \beta_{6\rho} SPP_{i,t-\rho} + \beta_{7\rho} SMP_{i,t-\rho} + \beta_{8\rho} FLP_{i,t-\rho} \\
&+ \beta_{9\rho} WNP_{i,t-\rho} + \beta_{10\rho} MinSpring_{i,t-\rho} + \beta_{11\rho} MinSummer_{i,t-\rho} \\
&+ \beta_{12\rho} MinFall_{i,t-\rho} + \beta_{13\rho} MinWinter_{i,t-\rho} + \beta_{14\rho} MaxSpring_{i,t-\rho} \\
&+ \beta_{15\rho} MaxSummer_{i,t-\rho} + \beta_{16\rho} MaxFall_{i,t-\rho} + \beta_{17\rho} MaxWinter_{i,t-\rho}) + d_i + c_i\}
\end{aligned}
$$

where

Φ = the standard normal cumulative density function;

i = 1, 2, … , N (state), t = 1, 2, … , T (time) , and ρ = 0, 1, … , m (lags number);

RISK = the risk of SPB outbreaks (the portion of timber volume killed by SPB in terms of the total volume of softwood growing stock);

USV = the portion of unsalvaged volume in terms of the total pine growing stock, which is measured as a percentage against growing stock and can represent human's efforts for adapting to climate change;

SPT = monthly average spring temperature;

SMT = monthly average summer temperature;

FLT = monthly average fall temperature;

WNT = monthly average winter temperature;

SPP = monthly average spring precipitation;

SMP = monthly average summer precipitation;

FLP = monthly average fall precipitation;

WNP = monthly average winter precipitation;

MinSpring = minimum spring temperature;

MinSummer = minimum summer temperature;

MinFall = minimum fall temperature;

MinWinter = minimum winter temperature;

MaxSpring = maximum spring temperature;

MaxSummer = maximum summer temperature;

MaxFall = Maximum fall temperature;

MaxWinter = maximum winter temperature;

d_i = state dummy variables; and

c_i = catastrophic events to filter out their effect.

March to May is the spring season, June to August is the summer season, September to November is the fall season, and December to February is the winter season. The independent variable *RISK* is calculated by using equation (4), and $0 \le RISK_{it} \le 1$. *RISK* implies the proportion of the timber volume killed by SPB in terms of the total pine species (Gan 2004).

(4) $$RISK_{it} = \frac{\text{Timber volume killed by SPB}_{it}}{\text{Total growing stock of pine species}_{it}}.$$

Lag variables are included in equation (3), as well as the current variables, to detect the lagged impact of climate conditions on SPB population/infestations (Gan 2004) because climate impact does not tend to appear immediately on SPB infestations (the past values of the variables). For example, last year's warm winter temperature can possibly influence the outbreaks of pine beetles in this spring. An *F*-test is used to determine the number of lags necessary for the model.

Data on the volume of trees killed by SPB are obtained from USDA Forest Service Southern Research Station (USDA Forest Service 2012b). The total growing stock of pine forests was obtained from forest inventory data (Smith et al. 2009). The forest inventory data are only collected every 5–10 years. Therefore, to generate annual series, linear interpolation is applied. Data for the years 1973 to 2004 for 11 southern states are used: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia. The average historical monthly temperature, precipitation, and monthly maximum/minimum temperatures are from the PRISM (Parameter-elevation Relationships on Independent Slopes Model) climate data (PRISM Climate Group 2013).

After obtaining the estimation results, marginal effects are calculated because in the GLM, the estimated coefficients are difficult to interpret. Marginal effects are defined as the effect of a unit change in one of the explanatory variables on y. Unlike linear regression approach, the estimated coefficients are not the same as marginal effects under the GLM framework. Marginal effects are calculated by taking a partial derivative of equation (3) with respect to x_k:

(5) $$\frac{\partial E(y|X)}{\partial x_k} = (g^{-1})'(X\beta)\beta_k .$$

The marginal effect for the probit link function follows equation (6) where ϕ is a probability distribution function of standard normal distribution:

(6) $$\frac{\partial E(y|X)}{\partial x_k} = (\phi)'(X\beta)\beta_k .$$

2.1.3 Assessment of climate change impact

Ongoing global climate change could directly influence tree health and the abundance of SPB populations. Global climate change causes more frequent and intensive climate events (e.g., droughts) and changes in biodiversity (Maclean et al. 2008). Therefore, climate change may affect the pattern of SPB risk. Several studies have investigated the link between climate and SPB risk (Gan 2004). Some studies claim that as the climate becomes warmer, large-scale insect outbreaks will become more common (USDA Forest service 2012a), but few studies examine quantitative relationships between future climate condition and SPB risk.

This study aims to assess the impact of future climate change on SPB risk using the estimation model and the future climatic factors projected by Global Climate Models (GCMs). The simulated future climate data from GCMs reflect the response of the global climate change to greenhouse gas (GHG) emission scenarios. GCMs based on the fifth phase of the Coupled Model Intercomparison Project (CMIP5) are applied to projecting future SPB risk under climate changes. These new GCMs have several

advantages. First, the new GCMs provide more unified metric, grid and location points than previous GCMs. Second, Representative Concentration Pathway (RCPs) scenarios in the new GCMs use scientifically specified terms to avoid ambiguous definition. For example, the special report on emission scenarios (SRES) based on the IPCC fourth assessment report (AR4) includes subjective components such as rapid economic growth and introduction of clean and resource-efficient technologies while the RCPs only consider the components of radiative forcing that is measured in W/m^2 (Wayne 2013). The RCPs scenarios are defined based on their total radiative forcing pathways. Cumulative measure of human emission of GHGs from all sources are expressed in Watts per square meter (IPCC 2013). The RCPs are: (1) RCP4.5: stabilization without overshoot pathway to 4.5 W/m^2 at stabilization after 2100; (2) RCP6.0: stabilization without overshoot pathway to 6 W/m^2 at stabilization after 2100; and (3) RCP8.5: rising radiative forcing pathway leading to 8.5 W/m^2 in 2100 (van Vuuren et al. 2011).

Several uncertainties emerge in predicting future climate such as model uncertainties and scenario uncertainties (Hawkins and Sutton 2009). To alleviate model uncertainty related to model bias, this study obtains six different climate models and then average out the climate variables from the different climate models including CanESM2, CCSM4, CESM1-CAM5, GFDL-CM3, HadGEM2-ES and MPI-ESM-MR under each RCP. These data are available at Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections (CMIP5 Climate and Hydrology Projections 2013). To alleviate scenario uncertainty, three RCPs including RCP4.5, RCP6.0 and RCP 8.5 are compared. In RCP4.5, which is a moderate but not extremely low emission scenario,

total radiative forcing is stabilized before 2100 while GHG emissions continue to increase through the 21st century in RCP8.5, the highest emission scenario (Stavros et al. 2014). Using forecasted climate data from the aggregated GCMs and different scenarios including RCP4.5, RCP6.0 and RCP8.5, this analysis projects future SPB risk for three time periods: 2012–2030, 2031–2060, and 2061–2090.

2.2 Cyclical patterns of SPB risk

2.2.1 Assessing cyclical patterns

To calculate "hidden" periodicities of SPB risk, periodogram analysis is applied. The periodogram is used to detect the dominant frequency and cyclical patterns in a time series. Historical SPB risk from 1973 to 2004 (base line scenario) and projected SPB risk from the year 2020 to 2099 by different models and scenarios are used as data for the periodogram analysis. Also, the Hodrick-Prescott (HP) filter is applied to calculate the periodogram (Hodrick and Prescott 1997). The HP filter method is a data-smoothing technique to reveal long-term trends by removing short-term fluctuations.

Consider the time series y_t that can be separated into two parts, $y_t = \tau_y + c_t$, where τ_t is the trend component, and c_t is the stationary component. The cyclical component is the difference between the original series and its trend (Hodrick and Prescott 1997). In the frequency domain approach, the stochastic cycles occur at frequency $\omega \in [-\pi, \pi]$. The spectral-density function, $f_y(\omega)$, specifies the contribution of stochastic cycles at each frequency ω. The time-series filter transforms the original series y_t into a new

series y^*_t which can be expressed as $y^*_t = \sum_{-\infty}^{\infty} \alpha_j y_{t-j}$. Thus, I can explain the spectral density of the filtered series $f_{y^*}(\omega)$ as the combination of the original series $f_y(\omega)$ and the filter weights α_j . This is

(7) $$f_{y^*}(\omega) = \left|\alpha(\exp(i\omega))\right|^2 f_y(\omega) .$$

I attempt to find a filter for which $f_{y^*}(\omega) = 0$ when unwanted frequencies occur and $f_y(\omega)$ is the desired frequency. Therefore, the ideal filter should be $\left|\alpha \exp(i\omega)\right|^2 = 0$ for unwanted frequencies and $\left|\alpha \exp(i\omega)\right|^2 = 1$ for desired frequencies. It is, however, hard to find such an ideal filter in practice, so I should consider the tradeoffs between the ideal filter and an implementable filter. The HP filter for a given λ follows equation (8) as follows:

(8) $$\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 .$$

The first term penalizes the cyclical component to minimize the sum of the squared deviations, and the second term is the sum of squared second differences in the trend component which panelize changes in the growth rate of trend. The smoothness of the trend component is related to λ . Therefore, the larger the λ , the smoother the trend component. Hodrick and Prescott (1997) say that usually a greater frequency of the data tends to need a larger value of lambda. They suggest $\lambda = 1600$ for quarterly data. Ravn and Uhlig (2002) suggest $\lambda = 129,600$ for monthly data and $\lambda = 100$ for annual data.

The graph of filtered time series only displays the estimated cycle components. Therefore, we need to plot the periodogram to see how well we have estimated the component. The periodogram is considered as an estimator of the spectral density function and displays the natural frequency and amplitude of the time series. The basic rule of thumb for interpreting the periodogram is that if a time series has a strong sinusoidal signal for some frequency, then the periodogram peaks at that frequency. If the data have non-sinusoidal signal for some frequency, then the periodogram peaks at that frequency (fundamental frequency) but also peaks at some multiples of that frequency (harmonic). For a pure random series, the periodogram will vary randomly around a constant.

The analysis procedure follows several steps. First, the evidence of periodicity in the data is established. The Bartlett Kolmogorov-Smirnov (BKS) test is performed to test whether the SPB risk follows a white noise or sinusoidal pattern. Then, the HP filter is applied method to smoothing the raw time series data. Finally, the periodogram is plotted using the smoothed data to display the frequency and amplitude of the data.

2.3 Results

2.3.1 Estimation results

To seek more statistical evidences for using probit link function, the deviances are calculated in the probit and logit link functions. The values of the parameters which minimize the deviance maximize the likelihood function (Hardin and Hilbe 2012). First, a same model is estimated using both logit and probit link functions. Then the deviance,

D, is calculated for each model. If the D of the probit model is significantly lower than that of the corresponding logit model, this is evidence that the probit model is superior to the logit model. Table 1 shows the calculated deviance statistics results. Because the model with the probit link function has a smaller deviance statistic than the model with the logit link function, using the probit link function is justified.

Table 1 Deviance statistics

	Probit	Logit
Log pseudo-likelihood	1354.30	1279.3
Deviance	0.00160	0.00268
AIC	-9.256	-8.742

The marginal effects of the estimated regression model are shown in Table 2. Because of the long list of independent variables, only the significant estimates are presented in Table 2 (full estimation results are shown in Table A1 in appendix). Heteroscedasticity and serial correlation are adjusted using robust standard errors. The robust standard error estimator relaxes the assumption of an independent and identically distributed error term. Several lagged seasonal temperatures and precipitations largely affect SPB risk in the current year. Previous studies found significant relationships between climate conditions of the previous year and the SPB outbreaks in the current year. Kalkstein (1981), for example, found that the previous winter temperature greatly affects the current spring outbreaks. To determine the lag order, Gan's method in his pine beetle study (2004) is chosen. First, the 10^{th} order lags model are compared with the

9^{th} order lags model using *F*-test. Remove 10^{th} lagged variable from the model if the test statistic is unable to reject the null hypothesis that the coefficient of the 10^{th} lagged variable is equal to zero. Then test 8^{th} order model against the 9^{th} order model. The procedure continues until the null hypothesis are rejected at a certain lag.

Table 2 Estimated results (marginal effects of GLM estimation): the relationship between SPB risk and independent variables

Variable description	Independent variable	Average marginal effect	Delta-Method S.E	*p*-value
Unsalvaged volume in current year	*USV*	0.0456	0.0127	0.0000
Spring temperature	*SPT*	0.0118	0.0051	0.0200
Fall temperature	*FLT*	-0.0141	0.0058	0.0500
Minimum winter temperature	*MinWinter*	0.0035	0.0015	0.0160
Summer temperature one year ago	*SMT1*	-0.0243	0.0092	0.0080
Fall temperature one year ago	*FLT1*	-0.0130	0.0061	0.0330
Winter precipitation one year ago	*WNT2*	-0.0006	0.0002	0.0100
Max winter temperature one year ago	*MaxWinter1*	0.0036	0.0014	0.0080
Max spring temperature two years ago	*MaxSpring2*	0.0088	0.0033	0.0070
Summer precipitation one year ago	*SMP1*	-0.0007	0.0003	0.0140

Note: Insignificant estimates at the 5% level are suppressed because of the long list of independent variables (full estimation results are presented in Table A1 in the appendix)

Unsalvaged volumes of trees, spring temperature and minimum winter temperature in the current year, minimum winter temperature one year ago, and maximum spring temperature two years ago have positive impacts on pine beetle outbreaks. However, the fall temperature in the current year, summer temperature one year ago, fall temperature one year ago, and winter precipitation one year ago have negative impacts on SPB risk. SPB infestation risk increases as spring temperature and minimum winter temperature rise due to early maturing beetle lavas. Warmer temperature in the spring and winter

could allow for faster development of the beetle population due to the increased the number of beetle generations completed (Gaylord 2014). Moreover, abundant food availability due to warmer spring temperature is also partially related to increases in SPB population because the host trees start to grow earlier and faster during the spring season (Gan 2004). The minimum winter temperature in the current year and one year ago are both positively related to SPB outbreaks. Continuous warming in consecutive winter seasons might be largely related to increases in the SPB outbreak risk. Continuously increasing winter temperature might cause a reduction in cold-induced beetle mortality (Bentz et al. 2010). The fall temperature has a negative impact on SPB because beetle larvae progressively develop cold tolerance during the fall due to accumulated cryoprotectant compound such as glycerol as temperatures decline during the season (Bentz and Mullins 1999). Increasing fall temperature, therefore, interrupts developing cold tolerance of the beetle larvae, and this could lead to a decrease in the SPB population due to higher mortality rates during the winter season. Summer temperatures one year ago have a negative impact on SPB infestation. A hotter summer in the previous year would reduce SPB infestation risk.

SPB infestation risk decrease as precipitation in the previous winter decreases and previous summer precipitation but the magnitude of precipitation impacts is smaller than that of temperature impact. Trees that suffer from water shortage are more exposable to SPB attacks (Gaylord 2014). Drought stress may reduce tree phloem thickness, and phloem thickness has been shown to be positively related to beetle brood production (Amman and Cole 1983). The unsalvaged timber also has a positive impact on SPB. The

unsalvaged beetles attacked stands can affect SPB infestations in the neighboring area. Especially, the unhealthy timbers are more susceptible to beetle attack because a healthy tree has more capacity to defend against attack such as exuding toxic resin to pitch out attacking beetles (Raffa et al. 2008). Thus, salvaging of tree killed by SPB help alleviate future infestation risk and maintaining healthy trees conditions could be one of the efficient management systems to reduce SPB damages.

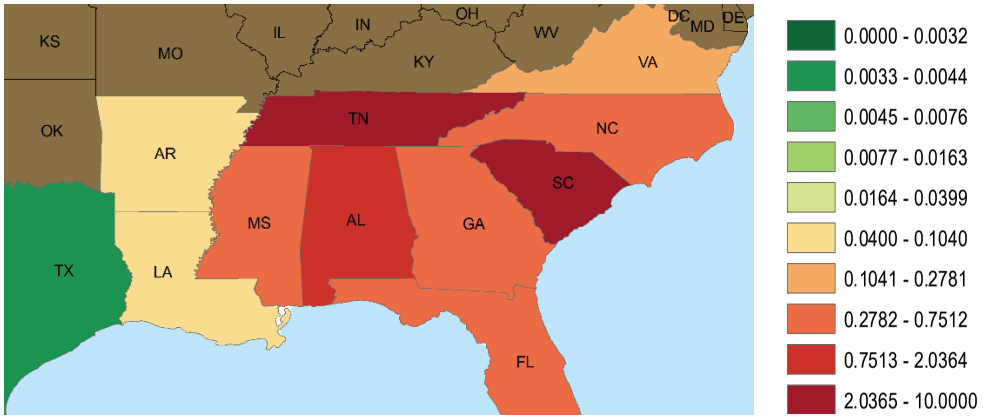
2.3.2 Climate change impacts on SPB risk

The predicted future temperatures from six different GCMs show that the southern U.S. is projected to be warm by 0.5 °F to 6 °F by the year 2098 compared to 2010, the base line. The projected temperature from the GCMs shows that spring, summer and fall are warming more than winter, but the model projections are more uncertain about if precipitation will be increasing or decreasing in this region by 2098. The precipitation change will vary depending on the scenarios and the regions, but the slight tendency towards wetter conditions can be detected in the middle part of the region including AL, MS, west LA, north GA and drying conditions in TX, north VA and FL. The projected averaged temperature and precipitation from 2020 to 2060 by different scenarios are shown in the figures A1–A5 in appendix. Compared to temperature and precipitation in the year 2010, we can detect a certain tendency toward increasing temperature but uncertain changes in precipitation.

Projected SPB infestation rate using aggregated GCMs for three time periods including 2012–2030, 2030–2060, and 2061–2090 for each RCP scenario is shown in

Figure 1. The values of projected SPB risk are expressed in ‰. The observed SPB risk in the period 1976–2004 is used as the baseline scenario. Although the projected SPB infestation varies across the climate change scenarios, SPB risks are predicted to be more severe in the short and midterm future (2012–2060, 2031–2060) than in the long term (2061–2098) for all scenarios. Also, the magnitude of damages varies across the regions. The center of the regions including northern AL, northern GA, north-western NC, western TN, and western VA will be exposed to more SPB risks compared to other regions under most of the climate scenarios. However, LA, eastern AR and part of eastern TX expect comparatively moderate SPB risks than other areas in most RCP scenarios. In the short term, SPB risk would slightly increase in the high emission scenario (RCP8.5), but SPB risk would decrease under the high emission scenario in the long term. Therefore, it is difficult to find a significant co-movement between scenarios and SPB risk. This result implies that the SPB population is determined by the complex interaction between precipitation and temperature. Higher temperatures tend to have a positive impact on SPB populations while higher precipitation level generally reduces beetle populations.

(a) SPB infestation rate from year 1976–2004: Base line scenario (‰)



(b) SPB infestation rate in 2012–2030: RCP4.5 (c) SPB infestation rate in 2012–2030: RCP6.0 (d) SPB infestation rate in 2012–2030: RCP8.5

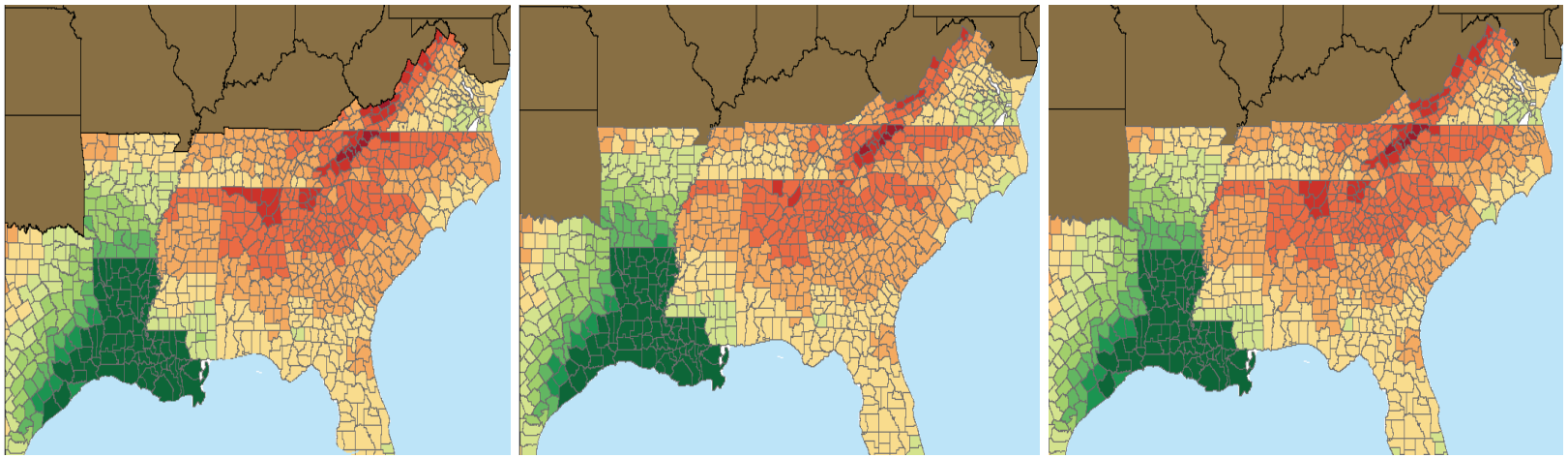
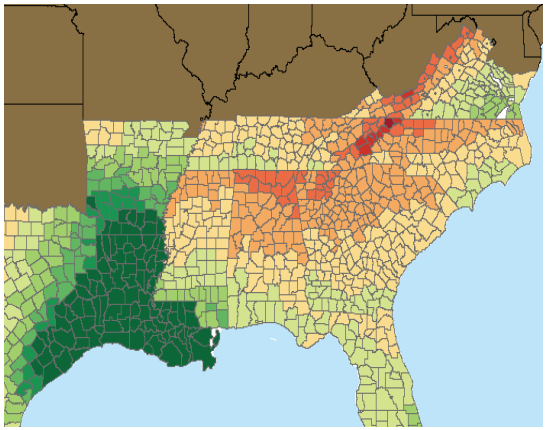
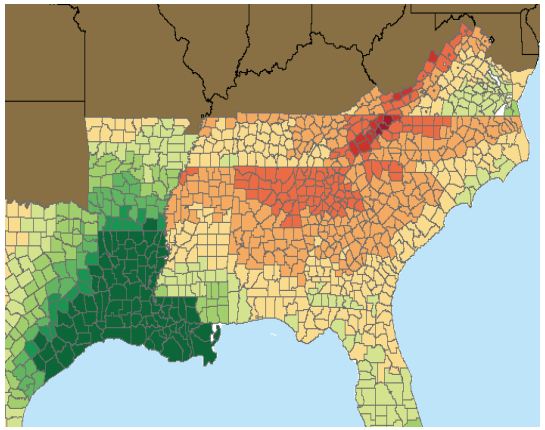


Figure 1 Projected SPB infestation rate by different scenarios (‰)

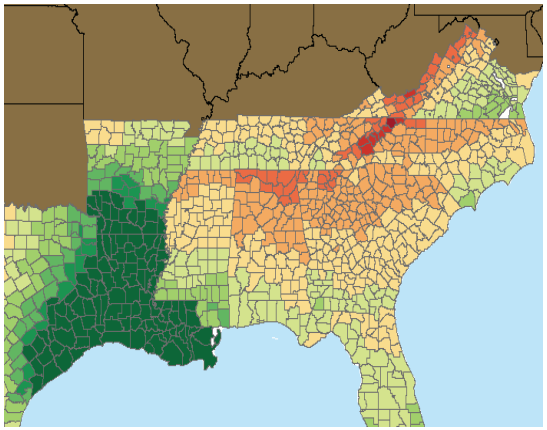
(e) SPB infestation rate in 2031–2060: RCP4.5



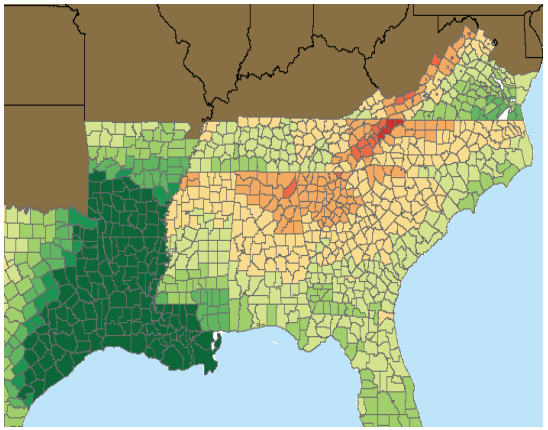
(f) SPB infestation rate in 2031–2060: RCP6.0



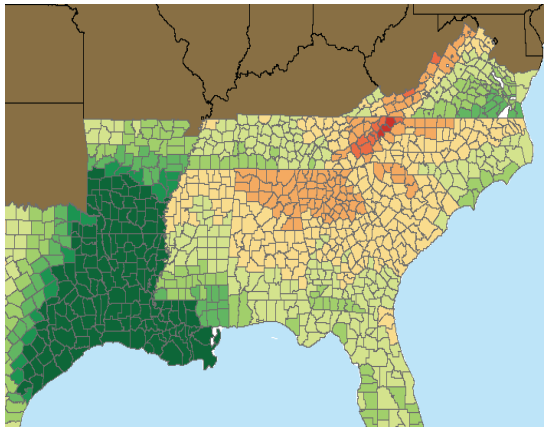
(g) SPB infestation rate in 2031–2060: RCP8.5



(h) SPB infestation rate in 2061–2098: RCP4.5



(i) SPB infestation rate in 2061–2098: RCP6.0



(j) SPB infestation rate in 2061–2098: RCP8.5

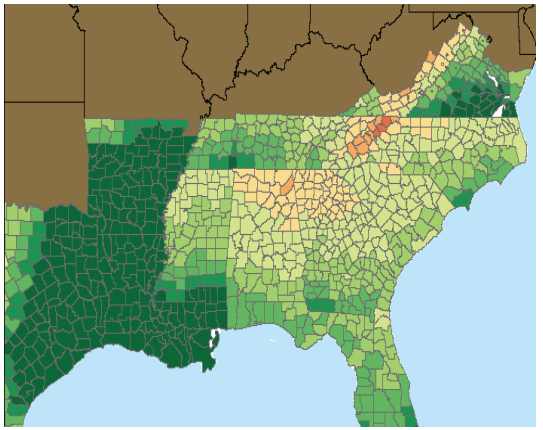


Figure 1 continued

In most scenarios, one can detect the increasing tendency of temperature but no specific co-movement between precipitation and temperature. In addition, the negative impact of hotter falls and summer could compensate the positive impact of warmer springs and winters on SPB infestation. Therefore, the magnitude of SPB infestation could be limited even if temperature shows an increasing tendency due to climate change. All in all, even if the global warming is ongoing, the risk of SPB outbreaks will not move in one direction. Rather the risk vary depends on the complex interactions between climate factors.

2.3.3 Cyclical patterns of SPB infestation

Base on the BKS test results in Table 3, the null hypothesis that the projected SPB infestation in a given state follows a white noise is rejected at the 5% significance level for every RCP scenario. This implies that the SPB infestation process is significantly different from white noise. For projected SPB risk, the existence of a deterministic sinusoidal component is detected for all states, while the null hypothesis of white noise fails to be rejected in several states based on the data of historical observations. At the 10% significance level, SPB infestations in LA, NC and TX show statistically significant evidence of a deterministic sinusoidal component.

Table 3 Bartlett Kolmogorov-Smirnov test result

State	RCP4.5	RCP6.0	RCP8.5	Historical
	BKS statistic (*p*-value)	BKS statistic (*p*-value)	BKS statistic (*p*-value)	BKS statistic (*p*-value)
AL	4.119 (0.00)	2.711 (0.00)	4.374 (0.00)	1.153 (0.14)
AR	3.386 (0.00)	2.489 (0.00)	3.608 (0.00)	0.887 (0.41)
FL	3.466 (0.00)	3.113 (0.00)	3.466 (0.00)	1.035 (0.23)
GA	4.120 (0.00)	2.723 (0.00)	4.110 (0.00)	0.418 (0.99)
LA	3.426 (0.00)	1.927 (0.00)	4.083 (0.00)	1.292 (0.07)
MS	3.937 (0.00)	2.471 (0.00)	4.270 (0.00)	1.210 (0.11)
NC	4.329 (0.00)	2.754 (0.00)	4.078 (0.00)	1.820 (0.00)
SC	3.922 (0.00)	2.655 (0.00)	3.815 (0.00)	0.736 (0.65)
TN	4.195 (0.00)	2.430 (0.00)	4.120 (0.00)	0.384 (0.99)
TX	2.733 (0.00)	2.894 (0.00)	4.246 (0.00)	1.343 (0.05)
VA	4.334 (0.00)	2.768 (0.00)	3.913 (0.00)	0.318 (1.00)

The amplitude and cyclical pattern of SPB infestation by scenarios are shown in Table 4. The amplitude and cyclical pattern are calculated by two different time periods, 2012–2060 and 2061–2098, because the patterns of projected SPB infestation risks differ between the short-term future and the long-term future. The outbreak period for historical SPB risks ranges from five to nine years. This implies that the SPB outbreak occurs every five to nine years. This result is supported by a study from Pye (1993). Pye (1993) noticed that SPB outbreaks reoccurred every six–seven years in the southern U.S. The projected SPB risk frequency is expected to be shorter than the observed risk (historical scenario). The frequency of projected SPB infestation risks varies across states, ranging from two to five years.

Two-tail *t*-test results, as shown in Table 5, indicate that most amplitudes and periods of projected SPB risk are different from those of the historical pattern. For amplitude, the test statistic rejects the null hypothesis that the projected amplitude of SPB is different from the historical one under all scenarios (at 5% level for RCP 4.5 and RCP 8.5, at 10% level for RCP 6.0) in the short term. However, the projected amplitude is not different from historical one in the long term because the test statistics fail to reject the null hypothesis. The projected periods of SPB risk are different from historical one under all scenarios, both in the long and short terms. Differences exist in periods of SPB risk rather than amplitude under climate change.

One-tail *t*-test results comparing between the amplitude of the projected SPB risk and the amplitude of historical SPB risk are presented in Table 6. The null hypothesis is that the amplitudes of historical SPB risk are larger than projected ones. For the short term, the null hypothesis is rejected. Therefore, the amplitude of SPB risk would increase in the short term future. However, in the long term, the null hypothesis that the historical amplitude is larger than projected one cannot be rejected. The statistical test results show that projected amplitudes are larger than the historical one in the short term. On the other hand, the projected amplitude is not larger than historical one in the long term.

Table 4 Amplitude and cyclical pattern of SPB risk: historical and scenarios

Scenarios			Year 2012–2060 (Short term)						Year 2061–2098 (Long term)					
	Historical		RCP 4.5		RCP 6.0		RCP 8.5		RCP 4.5		RCP 6.0		RCP 8.5	
State	Amplitude (Log Value)	Period (Year)	Amplitude	Period	Amplitude	Period	Amplitude	Period	Amplitude	Period	Amplitude	Period	Amplitude	Period
AL	1.40	6.45	1.60	2.45	1.20	2.53	1.80	3.30	1.00	3.08	1.20	2.93	1.20	2.65
AR	1.30	8.00	1.60	2.40	1.40	2.60	1.60	3.16	1.60	4.70	1.10	5.50	1.50	2.93
FL	1.00	5.41	1.40	5.40	1.50	2.11	1.80	3.30	1.30	2.74	1.50	3.35	1.30	2.47
GA	1.40	8.33	1.60	2.45	1.57	2.53	1.80	3.40	1.20	3.20	1.20	2.50	1.20	2.47
LA	1.00	8.33	1.00	8.16	1.10	4.75	1.00	8.00	1.10	3.17	1.00	5.50	1.00	2.47
MS	1.50	6.67	1.50	8.00	1.40	4.75	2.00	3.28	1.20	7.70	1.10	2.93	1.20	2.48
NC	1.40	6.45	1.60	2.45	1.30	2.53	1.50	3.28	1.00	7.60	1.60	2.80	1.20	2.48
SC	1.00	5.26	1.50	2.45	1.50	2.53	1.60	3.28	0.80	4.50	1.20	3.70	1.20	2.10
TN	0.80	4.55	1.50	2.45	1.40	4.00	1.60	3.28	0.80	4.50	1,5	2.90	1.30	2.90
TX	1.40	8.00	1.40	9.00	1.40	9.50	1.60	3.28	1.70	6.00	1.60	3.36	1.20	2.47
VA	1.00	9.50	1.50	3.50	1.60	4.22	1.20	9.00	0.80	7.70	1.80	2.95	1.40	2.11

Table 5 Two-tail *t*-test results for difference in the cyclical pattern and amplitude of SPB risk: historical vs. RCP scenarios

Scenario	RCP 4.5 Short term	RCP 6.0 Short term	RCP 8.5 Short term	RCP 4.5 Long term	RCP 6.0 Long term	RCP 8.5 Long term
p-value (Amplitude)	0.0030	0.0543	0.0007	0.4632	0.2400	0.6073
p-value (Period)	0.0127	0.0000	0.0000	0.0117	0.0007	0.0003

One-tail *t*-test results comparing between the cyclical periods of projected SPB risk and the cyclical periods of historical SPB risk are presented in Table 7. The null hypothesis is that the cyclical periods of historical SPB risk is shorter than projected one. The null hypothesis is rejected at the 5% significance level in both the short and long term. SPB outbreaks would be occurring rather frequently due to climate change.

Table 6 One-tail *t*-test results: historical amplitude > projected amplitude

Scenarios	RCP4.5 Short term Amplitude	RCP4.5 Short term Amplitude	RC8.5 Short term Amplitude	RCP4.5 Long term Amplitude	RCP6.0 Long term Amplitude	RCP8.5 Long term Amplitude
p-value	0.0015	0.0271	0.0003	0.7684	0.1241	0.3036

Table 7 One-tail *t*-test results: historical period < projected period

Scenarios	RCP4.5 Short term Period	RCP4.5 Short term Period	RC8.5 Short term Period	RCP4.5 Long term Period	RCP6.0 Long term Period	RCP8.5 Long term Period
p-value	0.006	0.000	0.000	0.006	0.000	0.000

2.4 Conclusions

I evaluate the impact of projected global climate change on the risk of SPB infestation using the GLM framework in this essay. This approach reduces the problems related to fractional response variables; especially the outcomes at the end points (zero and one) are allowed and the quasi-maximum likelihood can modify the assumption of the standard error. The estimation results indicate that average spring temperature, minimum winter temperature, maximum spring temperature a year ago, and maximum winter temperature a year ago have positive impacts on SPB infestation while spring and

winter precipitation a year ago, and average fall temperature have negative impacts on SPB outbreaks. The unsalvaged volume of trees killed by SPB also has a positive impact on SPB risk, implying that the human intervention can play an important role in reducing SPB infestation risk.

To project the relationship between SPB infestation and future climate change, aggregate averaged GCMs and three climate scenarios are used. This method may reduce uncertainties related to model bias. The projection results indicate that the risk of SPB outbreaks would not move in one direction given the complex interactions between temperature and precipitation. An increase in spring and winter mean temperature due to climate change would have a positive impact on SPB risk, but a rise in fall temperature and precipitation would tend to reduce SPB infestations. In general, the projection results show that in the short- and mid-term (2012–2060, 2031–2060), SPB risk is larger than in the long-term (2061–2098) for all RCP scenarios. However, the magnitude of damages varies across the southern region. Cyclical patterns of SPB outbreaks tend to change as global climate progresses. The historical cycle of SPB outbreaks re-occurred every six–seven years but this cycle is expected to take place more frequently, at a frequency of two–five years, under the projected climate change. Frequency and magnitude of SPB outbreak in the southern U.S. may respond to ongoing climate change. SPB risk is projected to severe in short-term and mid-term while the long-term climate change impact on SPB outbreaks is projected to be moderate.

The results of this essay reveal that the southern U.S. forests would be exposed to higher SPB risk in the short- and mid-term future (2012–2060, 2031–2060) than in the

long-term future (2061–2098). These findings suggest that continuously monitoring of SPB infestations is important in the south U.S. Salvaging beetle-damaged trees may help alleviate future infestation risk, and developing more effective SPB outbreak prevention and response measures are necessary. Also, policy makers should establish forest management strategies based on scientific prediction of climate change risk rather than their subjective estimates of those risks to protect forest disturbance by climate change.

This study has some limitations by the lack of fine-resolution historical data of SPB infestation. The state-level historical SPB data make it difficult to incorporate more detailed spatial variability into modeling. High-resolution historical SPB data can help improve the estimation of the relationship between SPB risk and climatic conditions. Another limitation is that the model assumes constant coefficients in the estimation and projection procedure. To assess dynamic climate impacts on SPB infestation risk in the long term, further studies would relax this assumption and apply time varying coefficients to estimations and projections of the SPB risk. Also, this essay could not consider the interaction impacts among climate variables. The interaction between temperature and precipitation might exist. It would be useful to add interaction terms to a regression model to understand the relationships among the climate variables in the future study.

3. THE EFFECTS OF CLIMATE AND CO_2 CONCENTRATION ON FOREST PRODUCTIVITY

In the U.S., about one third of the country's total land area is covered by forests (Smith et al. 2009). Forests provide commercial and non-commercial benefits to society including timber and other forest products, clean air, water, recreation, wild-life and carbon sequestration. Forest productivity, therefore, is always major concern for forest land managers and society. The growing body of literature that addresses the assessment of forest productivity is evidence of this concern. Recently, there has been an increasing interest in the climate change impact on forests. Climate plays a pivotal role in the structure and health of forest ecosystems. Moreover, there is evidence that ongoing climate change plays a crucial role in forest productivity (EPA 2013). Forests are under significant pressure from global climate change. Climate change may affect forest structure through a variety of pathways such as altering productivity and changing disturbance patterns (Vose and Klepzig 2013) that may bring about both positive and negative impacts on forest productivity.

Global climate changes can have positive impacts on forest resilience. Wu et al. (2014) found that climate warming is contributing a widespread growth enhancement of forest in British Colombia (B.C.) due to significantly increasing growing season length, especially in the high-latitudinal region B.C. Piao et al. (2006) studied the spatial patterns of vegetation growth over the North Hemisphere region using a mechanistic terrestrial carbon model. Their study showed that from 1980 to 2000, the increase in

vegetation in most of Siberia was associated with temperature warming while greening trend in North America was primarily related to the precipitation changes. However, they claimed that the contribution of rising temperature to the current enhancement of greening trend will be limited under continued global warming unless the higher moisture levels were accompanied with the higher temperatures.

Although several changes such as elevated CO_2 and warming temperatures accompanied with higher precipitation likely enhance forest productivity, climate change may negatively affect some forests. Temperature warming could have significant negative impact on forest if there are significant decrease in soil moisture and precipitation (Sedjo and Sohngen 1998). According to modeling study by Bowes and Sedjo (1993), the condition of natural forests in the U.S. Midwest is significantly dependent on precipitation. The productivity of forest would decline if climate warming and drying occur simultaneously while forest productivity would increase where warming coincided with increasing precipitation. Climate change also induces several other negative indirect impacts of forest productivity including wild fire and insect outbreaks (Kirilenko and Sedjo 2007). A number of authors have found that warmer temperature likely shifts the habit of forest insects such as pine beetle (Gan 2004; Bentz et al. 2010; Carroll et al. 2004).

Forest productivity is defined as the change in growing stock volume over time, usually measured by net volume per area (Vose and Klepzig 2013), and forest productivity is a common measurement of forest conditions at the stand level (Trumbore, Brando, and Hartmann 2015). Forest productivity is closely related to climate variables

including seasonal temperature and precipitation, as well as carbon dioxide (CO_2) concentration (fertilization), soil characteristics, forest density and structure. Climate factors affect many aspects of forest growth and productivity. Generally, forest productivity is higher in warm and moisture climates. The yearly average warming temperature because of climate change might move the forest zone farther north. So it is possible that some northern forest land in the U.S. will become more productive.

However, some tree species, tropical forest and high mountain forest in particular, will be at risk because their current geographical ranges are not suitable anymore if the current global warming trend is continued (Backlund, Janetos, and Schimel 2008). Increasing temperature could also influence the timing of snowmelt, which affects the seasonal water availability for trees (EPA 2013). Changes in precipitation will likely increase the risk of drought in some areas and the risk of extreme precipitation and flooding (EPA 2013). Drought also reduces trees' ability to protect them from destructive insects (Gaylord 2014).

Many studies have provided evidence of climate impacts on tree growth. Kiger (2014) examined the current growth of two dominant types of trees in European forests and found that trees are growing faster than they did in 1960. He believed that the current rising global temperatures and higher levels of CO_2 have accelerated tree growth. However, faster tree growth is not always a good thing because faster aging trees have relatively low wood quality (Taylor 2013).

Climate is also related to soil organic matter which is defined as decomposition product of organic materials in soil and is an important factor in forest productivity. An

increase in soil organic matter enhances crop/tree productivity, and the relationship between soil organic matter and crop or forest/tree yield is linear in most soil (Janzen, Larney, and Olson 1992). Level of soil organic matter is generally higher in the cool and humid regions or warm and arid regions because these conditions are favorable for soil microorganisms (Franzen et al. 2015). If water is sufficient, temperature warming will have a generally positive impact on forest productivity. Boisvenue and Running (2006) reviewed several papers reporting forest production levels, and 37 out of 49 studies showed a positive forest growth trend while five showed a negative trend, and three reported both a positive and negative trend for different time periods.

Beside the temperature factors, forest productivity is largely related to regional characteristics including biodiversity, soil conditions and tree density. Increasing atmospheric CO_2 concentration can stimulate forest productivity due to enhancing light and water use efficiency of the trees (Norby et al. 2005). Therefore, increasing CO_2 in the atmosphere will likely stimulate forest productivity if sufficient water and nutrients are available. However, the impact of increases CO_2 on tree growth is uncertain in limited water area (EPA 2013). The net forest productivity could increase in areas with high water availability. Water availability is related to not only precipitation but also depth of groundwater. Ford, Mitchell, and Teskey (2014) investigated the relationship between water table depth and aboveground net primary productivity (ANPP) of long leaf pines in the Southern U.S. They found that ANPP increases linearly with decreasing minimum annual water table depth. Shallow groundwater reduces water stress during dry years and mitigates decreasing net primary productivity associated with water

deficits (Soylu et al. 2014). If the water table, however, is too close to the surface during the growing season, the oxygen stress on roots can negatively affect photosynthesis (Soylu et al. 2014). Paquette and Messier (2011) examined the influence of biodiversity on forest productivity controlling for climatic and environmental conditions using stepwise regression to identify the relevant explanatory variables. According to the stepwise selection results, mean annual temperature, depth of the organic horizon, and basal area (BA) were significant in explaining forest productivity. Planting density was insignificant to forest productivity. In the slash pine forest, an increase in planting density decreased tree diameter growth. However, in contrast to individual tree growth, as stand density increases, the total wood production per unit area tends to increase because increasing total volume of tree production compensates for decreasing individual size (Ware and Stahelin 1948).

The climate change impact on forests may vary by the region. Especially, regions with limited water resources will tend to face amplified water losses because of warming temperature, and this might accelerate forest declines in these regions (Park Williams et al. 2013). On the other hand, regions with projected warmer temperature and higher precipitation are likely expected to have higher future forest productivity.

According to Rusted et al. (2011), higher temperature and increased CO_2 might lead to an increasing growth rate; the forests become more productive because trees absorbed more CO_2 from the atmosphere in the Northeast areas in the U.S. For the Western and Southeastern areas, on the other hand, warmer temperatures and the long growing season would have no crucial impact on tree productivity because of limited water availability.

Moreover, some tree species could not survive in the new climate conditions unless they move to higher altitudes (Rustad et al. 2011).

The purpose of this essay is to estimate the relationships between forest productivity and various independent variables including temperature, precipitation, soil, and tree density and using empirical modeling approach. Then, I will examine the future climate change impact on forest productivity across multiple global climate scenarios. The target area is all U.S. continental states. Although many studies have investigated the impact of climate parameters on forest productivity, the influence of specific climate parameters on forest productivity is still poorly understood. Moreover, regional specific changes of forest productivity under global climate change show large variability and direction of the changes are inconsistent between studies (Kirilenko and Sedjo 2007). There are two primary objectives of this essay: 1) to investigate the effects of climate change and forest characteristic on forest productivity using panel data analysis; and 2) to assess the future climate change impact on forest productivity using output from Global Climate Models (GCMs).

3.1 Data and model specification

3.1.1 Characteristics of U.S. forests and eco-climate zones

Forestland in the U.S. is widely but unevenly distributed with approximately 67 percent of all forestland is classified as timberland (Smith et al. 2009). The term timberland refers to "forest land capable of producing in excess of 20 cubic per year and not legally withdrawn form timber unitization" (Smith et al. 2009, 12). The continental

U.S. forests are concentrated in the South and Northeast, Pacific Northwest, the Lake states, and the Rocky Mountains while several central continental States including North and Dakota, Nebraska, Iowa, and Kansas have small proportions of forestland. According to Oswalt et al. (2014), overall trends of both acreages of forestland and timberland are upward nationwide between 2007 and 2014. Average net annual growth on growing stock trees has been increasing since 1996 in the North, South, and Pacific Coast region, but the growth has seen a decline in the Rocky Mountain region due to mountain pine beetle outbreaks (Oswalt et al. 2014). The definition of the forest reporting regions and subregions by states are shown in Table 8.

Table 8 Forest reporting region and subregion (Source: Smith et al. 2001)

Forest reporting region	Forest reporting subregion	States
Rocky Mountain	Interior Mountain	MT, ID, WY, NV, UT, VT, CO, AZ, NM
	Great Plain	ND, SD, NE, KS
Pacific Coast	Pacific North West	WA, OR
	Pacific South East	CA
North	North Central	MN, IA, MO, WI, IL, IN, OH, MI, MO
	North East	ME, VT, NH, MA, CT, NY, PA, WV, MD, DE, NJ
South	South East	VA, NC, SC, FL
	South Central	KY, TN, AR, OK, TX, LA, MS, AL

Forests in the U.S. are influenced by multiple climate and geographical factors including climate, geology, soil, and water (Smith et al. 2009). As such, the Forest Inventory and Analysis (FIA) program creates Ecoregion by grouped counties. An ecoregion is a broad area with climatic similarity that includes domain, division,

province, and section (Rudis 1999). There are four major eco-climatic domains in the U.S. including polar, temperature humid, arid and tropical humid (Bailey 1995). These eco-climatic zones are divided further subdivision by influence of precipitation: humid, semi-arid, arid (Smith et al. 2009). The major eco-climate domain in the U.S. continental areas is illustrated in Figure A6. The following discussion will introduce the major forest cover types and predominant climatic zones in the continental U.S. by geographic region.

The predominant climatic zone in the North region is temperate humid climatic zone. Oak-hickory and maple-beech-birch forests are dominant forest type in the North region (Smith et al. 2001; Oswalt et al. 2014). The predominant climatic zone in the South region is subtropical humid climatic zones expect for most of Kentucky and Tennessee (temperate humid) and a small area in south Florida (tropical humid). Loblolly-shortleaf pine forests are the major forest type in the South. Longleaf-slash pine forests are found in Florida, Georgia and the states bordering the South Atlantic and Gulf Coast (Smith et al. 2009). Longleaf slash pines have continued to decline due to wildfire and conversion of long leaf/slash pines to faster growing loblolly pines (Smith et al. 2001). The predominant climatic zone in the Rocky Mountain region is the temperate and subtropical arid and semi-arid climate zones. Pinyon-juniper forests are the dominant forest type in this region, mostly founded in Arizona, New Mexico, western Colorado, Utah and Nevada (Smith et al. 2009). Douglas-fir and Ponderosa-pine are found in the high elevation of this region. Climate zones of the Pacific Coast region include temperate oceanic, Mediterranean, temperature, temperate arid, and semi-arid.

Climate zones of the Costal Oregon and the Washington are temperate oceanic. Climate zones of the Western California is Mediterranean and the eastern portion of the region is mix of temperate and subtropical arid and semi-arid. The major forest types of the Pacific costal region are Douglas-fir, ponderosa pine, and western hard wood.

3.1.2 Data set for estimation and projection

For model estimation, the climate, forestry and soil data are necessary. County level historical climate and forestry data from 1990 to 2011 are used for all counties in the continental U.S. For estimation, county level data are grouped according to 150 ecological sub-regions, which have similar ecological characteristic (Rudis 1999). These ecological sub-regions are identified with a six-digit number developed by the U.S. Forest Service, Forestry Inventory and Analysis (FIA) based on the FIA hierarchical classification framework of ecological units for forest resource reporting purposes (McNab 2009). These numbers represent the domain, province, and section assigned to a U.S. county, based on the dominant ecological province and the dominant section within that province (Rudis 1999). The forest data are from Forest Inventory Data Online (FIDO) (USDA Forest Service 2015). Average annual net growth of growing-stock trees, area of forest land, tree count (number of growing stock trees) and above and belowground carbon in live trees are available in FIDO. The data and sources are explained in detail in Table A1. Soil data are from SSURGO database collected by the Soil Survey Staff, Natural Resources Conservation Service, United States Department of

Agriculture. Soil Survey is available online at the USDA web soil survey web page (NRCS 2013).

For historical temperature and precipitation, PRISM (Parameter-elevation Relationships on Independent Slopes Model) climate data are used. CO_2 concentrations in the atmosphere data are from the NOAA-GMD program and the data are available at the NOAA-Earth System Research Laboratory (Tans and Keeling 2014). CanESM2, CCSM4, CESM1-CAM5, GFDL-CM3, HadGEM2-ES and MPI-ESM-MR) and three climate scenarios are used. These GCMs data are available at the CMIP5 climate and Hydrology Projection web page (CMIP5 Climate and Hydrology Projections 2013).

3.1.3 Panel model specification test

Before proceeding to the model estimation, it is necessary to perform several tests on the data. First, the serial correlation of the data is tested. Under serial correlation in linear panel-data models, the estimation results become less efficient due to biases of standard errors (Drukker 2003). To detect possible serial correlation, the Wooldridge test for serial correlation in panel models (Wooldridge 2010) is used. The Wooldridge method uses the residuals from first differences. Consider the first differencing of the linear panel data model:

(10)
$$y_{it} - y_{it-1} = (x_{it} - x_{it-1})\beta_1 + \varepsilon_{it} - \varepsilon_{it}$$
$$\Delta y_{it} = \Delta x_{it}\beta_1 + \Delta\varepsilon_{it}$$

To detect serial correlations, I first regress Δy_{it} on Δx_{it} to estimate β_1 using equation (10) and obtain the error term $\hat{e}_{it}$. Then I regress the $\hat{e}_{it}$ on $\hat{e}_{it-1}$.

If there is no serial correlation, the coefficient on the lagged residuals is equal to -0.5.

Second, the independence of the error term across cross-sections is checked. In case of small time period, *T*, and relatively large sample size, *N*, Friedman (1937) and Pesaran (2004) test methods should be applied to test the null hypothesis of cross-sectional independence in panel-data models. If the test results reject the null hypothesis of cross sectional independence, it is necessary to take into account the cross sectional correlation.

The Wooldridge test result (F = 84.83; Pr = 0.000) rejects the null hypothesis of no first-order autocorrelation in panel data, indicating that the first order serial correlation exists in data set. Additionally, both Friedman (1937) and Pesaran (2004) tests reject the null hypothesis of cross-sectional independence at the 1% significance level, implying that the models are correlated across the panels.

3.1.4 Estimation method and model specification

To investigate climate and forest productivity, a panel data approach is employed. However, because the test results in previous section indicate the error terms are not i.i.d., applying the widely used Feasible Generalized Least Squares (FGLS) method to panel model is inappropriate because the standard errors generated from the FGLS method are extremely overconfident in the panel model. To overcome this problem, Beck and Katz (1995) suggested the OLS or Prais-Winsten estimates with panel correlated standard error (PCSE). If no autocorrelation is specified, this approach generates OLS estimates of the parameters. If correlation is specified, Prais-Winsten

estimates of the parameters are produced (Beck and Katz 1995). This approach allows for the errors term with heteroskedasticity across panels to autocorrelated within the panel. The parameters β are estimated by OLS if no autocorrelation is detected while the parameters are estimated by Prais-Winsten when autocorrelation is detected.

A panel data model for panel *i* and time *t* is

$$y_{it} = X_{it}\beta + \varepsilon_{it};\ i = 1,...,N;\ t = 1,...T, \tag{11}$$

where X_{it} is a vector of exogenous variables; y_{it} is the dependent variable; β is a vector of coefficients; and ε_{it} is the error term. Consider Ω is an $NT \times NT$ covariance matrix of the errors with elements $E(\varepsilon_{it}\varepsilon_{js})$. Then, the covariance of the OLS or Prais-Winsten coefficients is

$$\mathrm{Cov}(\beta) = (\mathrm{X}'\mathrm{X})^{-1}\mathrm{X}'\Omega\mathrm{X}(\mathrm{X}'\mathrm{X})^{-1} \tag{12}$$

If the errors follow spherical assumption (homoscedasticity and no correlation between observation), equation (12) becomes the standard OLS formula with $\widehat{\sigma^2}(\mathrm{X}'\mathrm{X})^{-1}$, where $\widehat{\sigma^2}$ is the error variance. However, this formula is not applicable unless the spherical error assumption is satisfied.

For a panel model with contemporaneously correlated and panel heteroscedastic errors, Ω can be expressed as $\Omega = \Sigma_{N\times N} \otimes \mathrm{I}_{T_i \times T_i}$ when the panel is balanced. Here, Ω is an $NT \times NT$ block diagonal matrix and Σ is an $N \times N$ matrix of contemporaneous covariances. To estimate equation (12), the elements of Σ are estimated using the formula, $\hat{\Sigma}_{ij} = \left(\sum_t e_{it}e_{jt}\right)/T_{ij}$, where $e_{i,t}$ is the OLS residuals (for panel i at time t), and

T_{ij} is the number of residuals between the panels i and j that are matched by the time period. Then $\hat{\Omega}$ is calculated by using $\hat{\Sigma}$.

The empirical regression model is

$$
\begin{aligned}
(13) \qquad y_{it} = {} & \beta_0 + \beta_1 CO2Air_t + \beta_2 Biomass_{it} + \beta_3 Biomass^2{}_{it} + \beta_4 Den_{it} \\
& + \beta_5 SPT_{it} + \beta_6 SMT_{it} + \beta_7 FLT_{it} + \beta_8 WNT_{it} + \beta_9 SPT^2{}_{it} + \beta_{10} SMT^2{}_{it} \\
& + \beta_{11} FLT^2{}_{it} + \beta_{12} WNT_{it}{}^2 + \beta_{13} SPP_{it} + \beta_{14} SMP_{it} + \beta_{15} FLP_{it} + \beta_{16} WNP_{it} \\
& + \beta_{17} SPP^2{}_{it} + \beta_{18} SMP^2{}_{it} + \beta_{19} FLP^2{}_{it} + \beta_{20} WNP^2{}_{it} + \beta_{21} SOI_i + \beta_{22} Drain \\
& + \sum\nolimits_j \beta_{23,j} ForType_{itj} + \varepsilon_{it}
\end{aligned}
$$

where

y_{it} = average annual net growth of growing stock volume in timber land (m^3 ha^{-1}yr^{-1});

i = ecological sub-region (150 in total);

t = year (1990–2011);

CO2Air = atmospheric CO_2 concentrations (ppm);

Biomass = above and belowground carbon in live trees (short ton) per hectare (ha) in timber land;

Den = tree density: (number of trees on timberland, per ha)

SPT = average spring temperature (°C);

SMT = average summer temperature (°C);

FLT = average fall temperature (°C);

WNT = average winter temperature (°C);

SPT^2 = square of spring temperature;

SMT^2 = square of summer temperature;

FLT^2 = square of fall temperature;

WNT^2 = square of winter temperature;

SPP = total spring precipitation (mm);

SMP = total summer precipitation (mm);

FLP = total fall precipitation (°C);

WNP = total winter precipitation (°C);

SPP^2 = square of total spring precipitation;

SMP^2 = square of total summer precipitation;

FLP^2 = square of total fall precipitation;

WNP^2 = square of total winter precipitation;

SOI = available water storage 0–50 cm in soil (Weighted average[1]);

Drain = soil drain class. 1 (poor drain) to 5 (excessively drain); and

ForType = forestry type. 1 (Longleaf/slash pine group), 2 (Loblolly/shortleaf pine group), 3(Oak/hickory group), 4 (Oak/Gum cypress group), 5(Maple beach birch), 6 (Pinyon-Juniper), 7 (Fir-spruce), 8 (Douglass-fir), 9 (Ponderosa-Pine), 10 (others).

To create eco-sub-region panel, first, obtain county-level forest and climate data then a six-digit sub-region code is assigned to each county. The numeric sub-region code assigned to individual counties is based on Rudis (1999). Finally, counties with the same sub-region code are grouped together to generate a sub-region panel. The first digit of

[1] The soil data reported is the weighted average of all components in the map unit (NRCS 2013).

sub-region code identifies the mountain and non-mountain province and next three digit identify the temperature domain. The last two digits identify a section[2].

The independent variable "average annual net growth" is used as measurement of forest productivity. Although there are a lot of indicator to assess forest productivity, there is a lack of a consistent definition of forest productivity (Grier et al. 1989). One of the widely used measurements of forest productivity is net primary productivity (NPP). NPP can be expressed as the sum of several components. That is $NPP = \Delta B - M - H - L - V$, where ΔB is the net standing biomass increment; M, H, L, and V are losses due to mortality, herbivory, leaching, and volatilization, respectively (Kloeppel, Harmon, and Fahey 2007). Among the NPP components, forest managers are concerned about biomass increments, that account for the weight and volume of wood, bark, foliage and roots (Grier et al. 1989). However, measuring NPP in forest ecosystems is a challenge because several components of NPP are difficult to quantify (Kloeppel, Harmon, and Fahey 2007). With this limitation, this study uses annual net growth of growing-stock volume timberland to measure forest productivity. Annual net growths have similar characteristics to NPP.

The formula for annual net growth is Annual net growth = Annual net change + Removal (USDA Forest Service 2015). The first component includes the increment in net volume of surviving trees plus the net volume of trees reaching the minimum size class minus the volume of trees that died and became cull trees during the specific year

[2] A section is a part of province with similar geomorphology, geologic origin, drainage networks, topography, and regional climate.

on the timberland (Oswalt et al. 2014). The second term identifies removed trees harvesting and/or thinning. Growing stock trees are defined as all live trees of commercial species that meet minimum merchantability standard (Oswalt et al. 2014). The average annual net growth can have a negative number because this value is net growth and the negative growth values are usually due to mortality but live trees also loss in volume because of damage, rot, broken top, or other reasons (Oswalt et al. 2014).

Biomass is defined as above and belowground carbon in live trees (short ton). The above and below ground carbon data is a measure of biomass above and belowground because carbon estimates can be converted to biomass estimates by dividing by approximately 0.05. This biomass variable represents an amount of a carbon sink[3] in forests (offsetting global greenhouse gas emissions) that helps offset fossil fuel emissions (Oswalt et al. 2014). Forest productivity is closely related to biomass because the biomass is related to nutrient availability in the site (Birks and Birks 2004). There is positive relationship between biomass and NPP but the relationship is rather quadratic, increasing at a decreasing rate and then declining after a peak point (Keeling and Phillips 2007). To reflect this relationship, the model includes the square term of the biomass variable.

CO2Air is included to account for the impact of the increasing CO_2 concentration in the atmosphere at the global level. From 1978, CO_2 concentration in the atmosphere have gradually risen and reached 380ppm in 2013. The CO_2 variable measures the

[3] Carbon sink of above ground biomass could be calculated using allometric equation (Chave et al. 2006). The equation from Mokany et al. (2006) could be used to estimate carbon stock below ground.

carbon fertilization impact on forest productivity. Previous study evaluating the growth enhancement induced by carbon is 8.4–21.6 % in four major plantations from 1980 to 2005 in Japanese forests (Fang et al. 2014). Seasonal temperature, precipitation, and square terms of seasonal temperature and precipitation are included to detect the nonlinear relationships between forest productivity and climate variable variables.

SOI indicates available water storage with the depth of 0–50 cm in soil from the surface. It is an indicator of soil's ability to store water within the plant's root zone. Available water storage is determined by soil texture, abundance of rock fragments, soil depth and layers, and plant rooting depth (USDA NRCS 2008). Applying more water to the soil than its water storage capacity brings about leaching of nutrients beyond the root zone because of loss of water to deep percolation (Nyvall 2002). The soil drain class represents free water in soil. The coding of soil drain classes ranges from 1 to 5, including 1= poor drain, 2= moderately well drain, 3= well drain, 4= somewhat excessively drain, and 5=excessively drain. Excessively drain soil has very low available water storage capacity. The excessively draining soil is usually very sandy or gravely and has rapid surface flows during heavy rainfall (Soil Survey Staff 1993). Poorly draining soil usually has dark gray to black color. Soil moisture in poor draining soil is not largely affected by precipitation changes because excess water is available during a large part of the time (Agriculture and Agri-Food Canada 2013).

The *ForType* variable is categorical representing the most dominant forest cover species in the target region. The major forest cover types in the Northern region are Maple beech birch, Oak-hickory, and Spruce-fir. Oak-hickory is the main forest cover in

the central and south region of the North. Maple beech birch forests include valuable hard wood species and account 31 percent of all north forests. Loblolly-shortleaf are the most predominant species in the Southern forest. Longleaf-slash pine, Oak gum cypress and Oak hickory are also major forest type in the Southern forests. Douglas fir, Ponderosa Pine, and Pinyon Juniper are major forest cover in Pacific Coast region. Douglas fir grow in magnificent in the coast of the Pacific Northwest.

3.1.5 Assessment of climate change impact on forest productivity

Climate change directly and indirectly influences tree productivity through changes in temperature, precipitation, and carbon concentration in the atmosphere.

Aggregate average of six different climate models including CanESM2, CCSM4, CESM1-CAM5, GFDL-CM3, HadGEM2-ES and MPI-ESM-MR and three different climate scenarios including RCP4.5, RCP6.0 and RCP8.5 are applied to the assessment of climate change impacts on tree productivity. These are the same models and scenarios in the SPB analysis in the previous section. Future forest productivity for three time periods: 2012–2030, 2031–2060 and 2061–2090 are projected. The estimated coefficients from equation (13) are directly applied to the GCMs and the scenarios to calculate the future forest productivity changes. To project future CO_2 concentration impacts on the productivity, we consider the future CO_2 will change according to the following assumption. CO_2 consternation in the atmosphere has been continuously rising from 315ppm in 1959 to 338 ppm in current year. CO_2 concentration projected to steadily increase and reach, 500–1000 ppm, by the year 2100 (IPCC 2007). The

projected CO_2 concentration is represented by several RCP scenarios: (1) RCP4.5: CO_2 concentration in the atmosphere will continuously increase to 520 ppm by 2070 then continue to increase but in a slower pace to reach 530 ppm by year 2100, (2) RCP6.0: CO_2 concentration will increase slowly then reach 620 ppm by 2100, and (3) RCP8.5: This is the extreme scenario, where CO_2 concentration in the atmosphere will dramatically increase and, reach 950ppm by 2100, approximately three times more than its than current level. All of these three CO_2 concentration scenarios are described detail in Meinshausen et al. (2011).

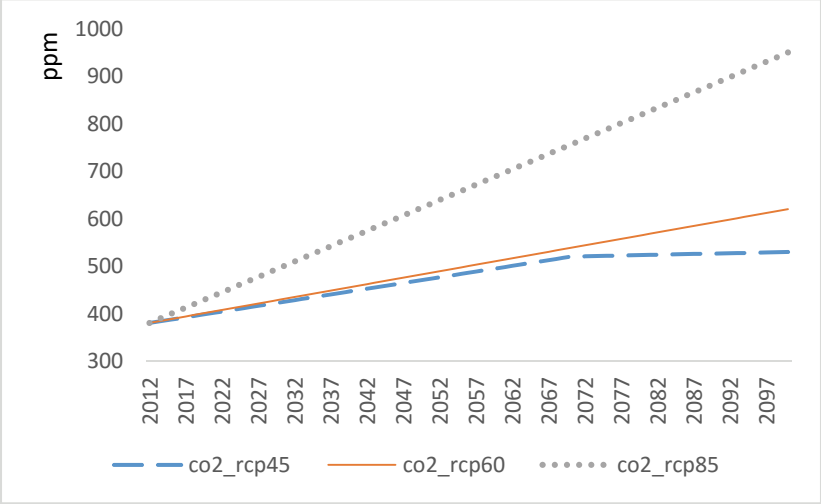


Figure 2 CO_2 concentrations by scenario (ppm)

Rising CO_2 concentrations are likely to have a direct effect on the forest growth, physiology and chemistry, depending of its effects on climate (Ziska 2008). Increasing CO_2 concentration has some positive impact on plants such as maintaining high photosynthesis rates with relatively lower stomatal conductance (Taub 2010). However,

the benefit from extra CO_2 is limited. The Free-Air CO_2 Enrichment (FACE) experiment shows that plant growth is elevated at the 475–600 ppm CO_2 concentration level due to increasing leaf photosynthetic rate (Ainsworth and Rogers 2007). Another study using the FACE experiment also found that 40% and 29% enhancements of photosynthesis are detected at the 500 to 600 ppm CO_2 concentration level (Ellsworth et al. 2004). Drake, Gonzàlez-Meler, and Long (1997) found that there would be 23% and 58% enhancements of photosynthesis when plants were grown at the 500 to 600 ppm CO_2 concentration level. Danyagri and Dang (2014) investigated the relationship between the change in CO_2 concentrations in the atmosphere and the performance of mountain maple (*Acer spicatum L.*). They found that the magnitude of biomass response to light was the lowest under a higher CO_2 concentration (784 ppm) and warmer soil. These results suggest that too elevated CO_2 concentrations due to climate change might have a negative impact on the forest canopy of mountain maples. Together, these results suggest that there is a positive association between CO_2 concentration and forest productivity but the CO_2 fertilization impacts are limited to a certain CO_2 concentration level (more than 600 ppm or 700ppm) in the atmosphere. Considering this, this study generates future CO_2 concentration levels using IPCC scenarios (Figure 2), but sets a ceiling on the CO_2 fertilization effect at 650 ppm. In other words, this study assumes that there is no more benefit from CO_2 fertilization if the concentration level is more than 650 ppm (Pessarakli 2014).

3.2 Results

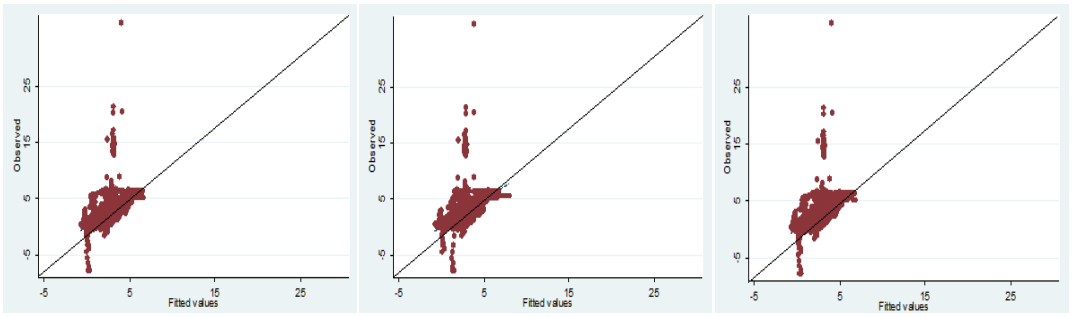
3.2.1 Estimation results

To estimate the relationship between forest productivity and independent variables, I perform estimation based on both linear and quadratic equations and using stepwise estimation equation approach. Equation (13) is used for quadratic estimation. For linear estimation, the squared terms of temperature and precipitation are removed from equation (13). The stepwise approach involves several steps. First, I run estimation using equation (13), Second, statistically insignificant variables are removed one by one based on significance of coefficients using *p*-value at 10% significance level (Paquette and Messier 2011).

PCSE does not provide a log-likelihood value because the statistical assumptions of PCSE does not equal to the assumption in OLS or Prais-Winsten model used to calculate the likelihood function. Therefore, R^2, observed and fitted plots, and mean squared error are used to compare model fit. The plot of the observed and fitted values of forest productivity from the quadratic equation, linear equation, and stepwise approach is shown in Figure 3. The x axis indicates the fitted values from estimation and the y axis indicates the observed values form data. The fitted values from linear estimation seem to slightly under estimate the observed values. The plot of the observed values against the fitted one by region and forest type are shown in the Figures A7–A12. Table 9 shows the root mean square error and R^2 from each estimation. The linear estimation has the highest R^2, but also has the highest mean squared error. Together these results reveal that

the quadratic estimation is the better choice than linear or stepwise based on quadratic equation approach for the model.

(a) Quadratic equation (b) Linear equation (c) Stepwise equation



$\hat{y}$ =1.39+0.43y, R^2=0.47
RMSE: 1.09

$\hat{y}$ =1.56+0.41y, R^2=0.42
RMSE: 1.13

$\hat{y}$ =1.41+0.42y, R^2=0.46
RMSE: 1,89

Figure 3 Observed vs. fitted plot

Table 9 Root mean squared error and R^2 from each estimation

	Root Mean Squared Error	R^2
Stepwise estimation	1.741	0.47
Quadratic estimation	1.732	0.53
Linear estimation	1.796	0.57

Table 10 shows the PCSE estimation results of regression including quadratic temperature and precipitation terms. Because of the quadratic terms of seasonal temperature and precipitation are included in the model, the marginal effects of climate variables on forest productivity are not constant but vary across the range of the

variables. There is an association between climate and forest productivity. Increasing fall and winter precipitation is likely to lead to a significant increase in forest productivity ($p < 0.05$ for winter precipitation, $p < 0.10$ for fall precipitation), and the quadratic terms of fall and winter precipitation are not statistically significant. There is also a positive relationship between forest productivity and spring, fall and winter temperature while a negative relationship exists between forest productivity and spring temperature square and fall temperature square. These results imply that the relationship between forest productivity and, spring and fall temperature is concave rather than linear. The marginal impact of temperature, precipitation, and biomass are shown in Figure A13 in appendix. Only the variables having statistically significant square terms are shown in the Figure A13 because the linear relationships are easily interpreted to use Table 10.

In Figure A13, as spring temperatures increase, forest productivity increases at a decreasing rate. Likewise, as fall temperatures go up, forest productivity increases at a decreasing rate. The linear and square terms of winter temperature are both positive. This implies that forest productivity responds to increasing winter temperature at an increasing rate but the magnitude of increment in marginal effect of winter temperature on forest productivity is not huge because the coefficient value of square term is small. The linear term of summer precipitation has a positive sign while the square term of summer precipitation is negative. This implies that forest productivity could be decreased at a decreasing rate as summer temperatures increase. However, because of the small value of coefficient for square term, the relationship is close to being linear. Forest productivity is increased with higher biomass at a decreasing rate.

Table 10 Estimation result with quadratic temperature and precipitation terms

Variable description	Independent variables	Coefficient	Panel Correlated Std. Error	*p*-value
density	*Den*	**0.030679**	**0.004393**	**0.000**
Biomass	*Biomass*	**0.082904**	**0.020086**	**0.000**
Biomass2	*Biomass2*	**-0.001536**	**0.000685**	**0.025**
CO_2 in Air	*CO2Air*	**0.010857**	**0.005078**	**0.032**
Spring Precipitation	*SPP*	-0.000482	0.000967	0.618
Summer Precipitation	*SMP*	**-0.005936**	**0.001208**	**0.000**
Fall Precipitation	*FLP*	**0.001489**	**0.000806**	**0.065**
Winter Precipitation	*WNP*	**0.002054**	**0.000568**	**0.000**
Spring Precipitation^2	*SPP2*	0.000001	0.000001	0.334
Summer Precipitation ^{2}	*SMP2*	**0.000007**	**0.000002**	**0.000**
Fall Precipitation ^{2}	*FLP2*	-0.000002	0.000001	0.107
Winter Precipitation^2	*WNP2*	-0.000001	0.000000	0.104
Spring Temperature	*SPT*	**0.189883**	**0.053003**	**0.000**
Summer Temperature	*SMT*	0.016669	0.147115	0.910
Fall Temperature	*FLT*	**0.240033**	**0.053679**	**0.000**
Winter Temperature	*WNT*	**0.098559**	**0.018442**	**0.000**
Spring Temperature^2	*SPT2*	**-0.010937**	**0.003177**	**0.001**
Summer Temperature^2	*SMT2*	-0.003458	0.003630	0.341
Fall Temperature ^{2}	*FLT2*	**-0.007564**	**0.002704**	**0.005**
Winter Temperature^2	*WNT2*	**0.002698**	**0.001109**	**0.015**
Available Water Storage 0–50 cm	*SOI*	**0.317386**	**0.044639**	**0.000**
Soil Drain class	*Drain*	**-0.236042**	**0.064133**	**0.000**
Forest Type	*ForType*			
Longleaf/ Slash	*1*	0.050	0.283	0.859
Oak/ hickory	*3*	-1.354	0.285	0.000
Oak/Gum cypress	*4*	-1.661	0.180	0.000
Maple beach birch	*5*	-2.161	0.360	0.000
Pinyon juniper	*6*	-2.458	0.278	0.000
Fir spruce	*7*	-3.739	0.332	0.000
Douglass fir	*8*	-2.329	0.342	0.000
Ponderosa pine	*9*	-1.473	0.377	0.000
Other	*10*	-2.697	0.398	0.000
Constant	*Constant*	-2.848	2.410	0.237
R-square				0.531
Number of observations				3278

There is no statistically significant relationship between forest productivity and summer temperature at the 5% level. Frost damage caused by cold winter could be

prevented by a 2 ºC winter temperature increase (Kirschbaum 2000). Johnson, Cook, and Siccama (1988) indicated that the winter damage such as freezing injury is an important factor in red spruce decline between mid-1960s and mid-1980s in the mountain of New York and western England. Also warmer winter temperature enhances microorganism activity in the soil. It has been suggested that microorganism have limited ability to sequester substrates at cold temperature around 0 °C (Drotz et al. 2010). Therefore, increase in winter temperature would enhance forest productivity due to protecting winter damage and enhancing microorganism in soil.

Positive relationships between forest productivity and spring and fall temperatures might be largely related to growing season length. Warmer spring and fall temperature could extend tree growing seasons. However, too high temperature during spring and fall season may increase the rate of respiration. If the rate of reparation level exceeds the optimum level, that might cause death of the tree (Hawkins et al. 2008). Grace and Zhang (2006) suggest that if annual temperature reaches 10–14 °C, net ecosystem productivity would be negative, under both normal and double CO_2 concentration level, based on data from the boreal forest. Spring temperature is also related to snowpack melt. Usually, warming spring temperature can cause melting snowpack earlier than usual. The early melting increases soil frizzing in spring. This may possibly offset the positive effects of warming by damaging roots (Templer 2015). Way and Oren (2010) found that increased temperatures generally increase tree growth, except for tropical trees. The temperature effects on tree growth might be related to the effects of temperature on tree cell division and expansion (Körner 2003). Plant cells at higher

temperatures tend to divide more rapidly than at lower temperatures in spite of having same length of the cells (Bertin 2005). Temperature is also related to tree growing season length. For example, every 1 °C increase in average annual temperature leads to an increase in growing season length by five days in the eastern U.S. (White, Running, and Thornton 1999). Few studies investigate the direct impact of increased growing season length on forest productivity. The bud burst growth model simulations suggest that there is a positive relationship between the timing of bud burst, consequently, length of growing season, and tree growth (Menzel and Fabian 1999).

The estimation results in this essay also confirm that seasonal precipitation is an important determinant of forest productivity. Even though forest productivity increases with an increase in temperature, patterns of precipitation in a changing climate may alter forest productivity (Way and Oren 2010). Positive correlations are found among density, CO_2 concentration in the atmosphere and forest productivity. The negative relationship between summer precipitation and forest productivity is related to flooding. Summer is usually the season with high precipitation. Increase in summer precipitation could lead to increase in flooding frequencies during summer season. Flooding could have negative impact on forest precipitation by increasing soil erosion. Short-duration floods might enhance forest productivity in wetland by providing additional water and nutrient while long-term flooding decrease forest productivity because of the physiological stress with anoxic soil condition (Megonigal et al. 1997). Increasing CO_2 concentration in the atmosphere has positive impacts on forest productivity because CO_2 in the air directly affects to plant. Increasing CO_2 concentration in the atmosphere enhances

photosynthesis of trees and makes more efficient use of soil moisture (Wigley, Briffa, and Jones 1984). The recent increment of growth in the several high altitude forests might be directly related to current increasing trend of CO_2 concentration in the atmosphere (Lamarche et al. 1984). Available water storage has a positive impact on the forest productivity while soil drain class has a negative impact on forest productivity. This result indicates that forest productivity is also significantly related to not only temperature but also soil water availability and soil moisture. In terms of forest type, the loblolly-slash pine forest shows higher productivity than any other forest type. Loblolly pines are fast growing trees, but these results also imply that the loblolly and slash pines could respond better to climate change than other major tree species in the U.S. in terms of annual net growth of merchantable timber.

The PCSE estimation results of regression without quadratic temperature and precipitation terms are illustrated in Table 11. A significant ($p < 0.05$) positive correlations is found between fall precipitation, winter precipitation, fall temperature, winter temperature and forest productivity. For a 1mm increase in total fall precipitation, forest productivity would increase by 0.0008 m^3 $ha^{-1}yr^{-1}$. For a 1mm increase in total winter precipitation, forest productivity would increase by 0.0020 m^3 $ha^{-1}yr^{-1}$. On the other hand, a 1 mm increase in summer precipitation would reduce the forest productivity by -0.0020 m^3 $ha^{-1}yr^{-1}$. For a 1 °C increase in fall temperature, forest productivity would increase by 0.0943 m^3 $ha^{-1}yr^{-1}$. For a 1°C increase in winter temperature, forest productivity would increase by 0.0823 m^3 $ha^{-1}yr^{-1}$. There are positive correlations detected between density, CO_2 in the atmosphere and forest productivity. As

CO_2 in the atmosphere increases 1 ppm, forest productivity would increase by 0.0115 m^3 $ha^{-1}yr^{-1}$. The forest productivity could be increased as biomass is increased but at a decreasing rate.

Table 11 Estimation result without quadratic temperature and precipitation terms

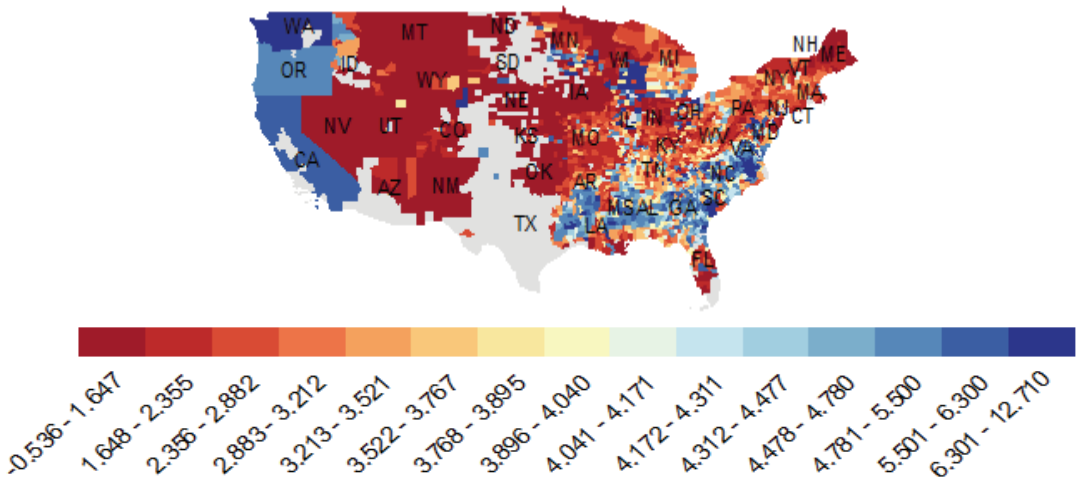
Variable description	Independent variable	Coefficient	Panel Correlated Std. Error	*p*-value
density	*Den*	0.0298	0.0045	0.00
Biomass	*Biomass*	0.0639	0.0308	0.04
Biomass^2	*Biomass2*	-0.0011	0.0009	0.22
CO_2 in Air	*CO2Air*	0.0115	0.0055	0.04
Spring Precipitation	*SPP*	0.0002	0.0004	0.57
Summer Precipitation	*SMP*	-0.0020	0.0005	0.00
Fall Precipitation	*FLP*	0.0008	0.0004	0.04
Winter Precipitation	*WNP*	0.0020	0.0003	0.00
Spring Temperature	*SPT*	0.0140	0.0340	0.68
Summer Temperature	*SMT*	-0.1728	0.0339	0.00
Fall Temperature	*FLT*	0.0943	0.0327	0.00
Winter Temperature	*WNT*	0.0823	0.0172	0.00
Available Water Storage 0–50 cm	*SOI*	0.3435	0.0451	0.00
Soil Drain class	*Drain*	-0.2612	0.0641	0.00
Forest Type	*ForType*			
Longleaf/ Slash	*1*	-0.4958	0.2419	0.04
Oak/ hickory	*3*	-0.5395	0.3154	0.09
Oak/Gum cypress	*4*	-2.1159	0.1962	0.00
Maple beach birch	*5*	-1.1575	0.2218	0.00
Pinyon juniper	*6*	-1.4069	0.2776	0.00
Fir spruce	*7*	-2.6579	0.2779	0.00
Douglass fir	*8*	-1.1751	0.3112	0.00
Ponderosa pine	*9*	0.0077	0.2832	0.98
Other	*10*	-1.3826	0.3228	0.00
R-square				0.572
Number of observations				3278

3.2.2 Climate change impacts on forest productivity

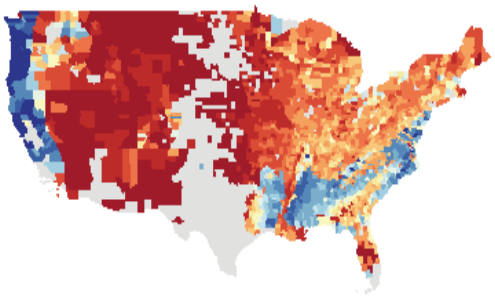
Projected future forest productivity using aggregated GCMs for three time periods including 2012–2030, 2030–2060 and 2061–2090 under each RCP scenario is shown in Figure 4. The observed forest productivity in the period 1990–2011 is used as the baseline scenario. The historical base line map shows that high forest productivity is mostly located in the South (Southeast and Southcentral) and Pacific coast (Pacific southwest and Pacific south east) forest regions while the arid Rocky mountain region (Inter-mountain and the Great Plains) has low forest productivity. The increasing trend of forest productivity is expected in the South and Pacific coast forest regions. Especially, ample precipitation in the humid area of the Pacific costa region is expected with a continuous increasing trend of forest productivity both in the long term and the short term under all RCP scenarios.

In the short term (2012–2030), high forest productivity would be anticipated in the South and Pacific coastal regions. However, the Rocky Mountain region would have low forest productivity. The South and Pacific coast regions are expected to have high forest productivity in the mid-term (2031–2060) and the long term (2061–2098) in all climate scenarios. Several South states including LA, AL and SC show an increasing trend of productivity with each climate scenario in all three future time period. Productivity gains in these areas might be caused by expanding growing season, water availability and carbon dioxide fertilization due to increasing temperature, precipitation, and CO_2 concentrations in atmosphere as result of projected climate change.

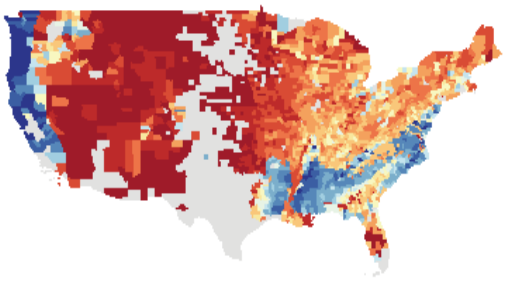
(a) Annual average forest productivity 1990–2011: Base line scenario



(b) RCP4.5: Years 2012–2030



(c) RCP6.0: Years 2012–2030



(d) RCP8.5: Years 2012–2030

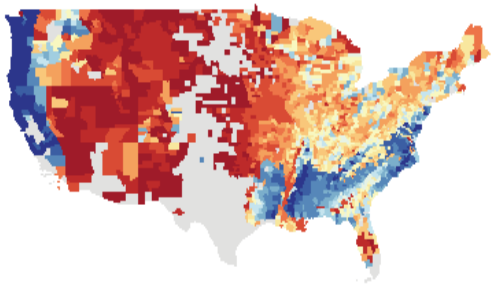
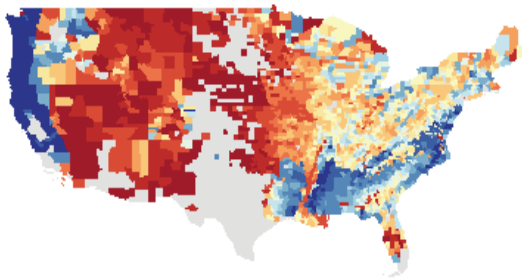
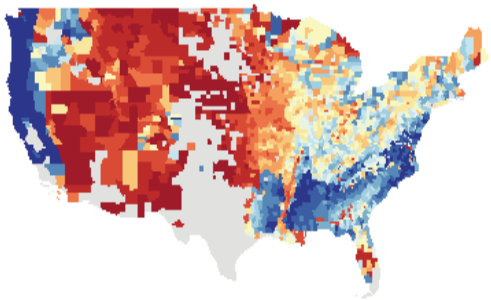


Figure 4 Projected forest productivity under different climate scenarios (m3/ha/yr)

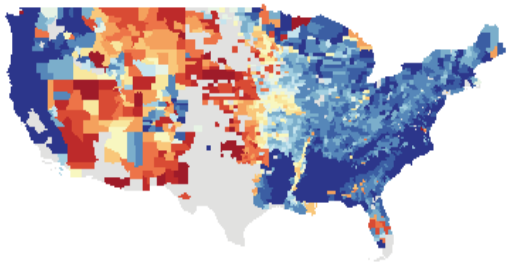
(e) RCP4.5: Years 2031–2060



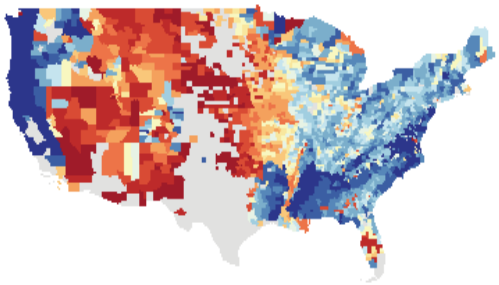
(f) RCP6.0: Years 2031–2060



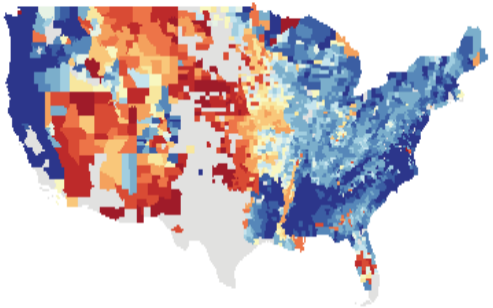
(g) RCP8.5: Years 2031–2060



(h) RCP4.5: Years 2061–2098



(i) RCP6.0: Years 2061–2098



(j) RCP8.5: Years 2061–2098

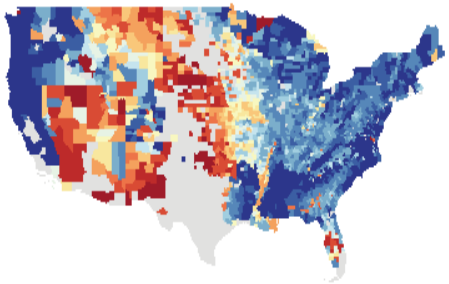


Figure 4 continued

However, the sub-tropical region in the southern FL are expected to have low forest productivity due to decreasing precipitation. Most of eco-climate zone in southern FL is sub-tropical and tropical forest; tropical forests are vulnerable to a warmer climate (Malhi et al. 2008).

The forest productivity in the North (Northeast and Northcentral) would also increase in the long term under both low and high emission scenarios. The North forest might be largely affected by climate changes. Several long term climate datasets indicate that the temperature and precipitation in the Northeast region have become warmer and wetter (Hayhoe et al. 2006), and the climate models predict that the region would become even warmer and wetter in the future. Winter temperatures in the region are expected to increase significantly. The Great Plains apparently has been affected by climate change over the last few decades. Record preserved in tree rings, sediments, and sand deposit have shown evidence of expanding drought and altering wetter conditions (Woodhouse and Overpeck 1998). The historical record of low forest productivity might be affected by this trend. In the Great Plains, temperature is expected to continuously increase over this century.

Precipitation changes are also projected but the changes would vary across the region. The northern part of the Great Plains would become wetter, but the southern part would be drier. Therefore, forest productivity in northern Great Plains is projected to increase while lower forest productivity is projected for the southern Great Plains. Increasing forest productivity is projected in some part of east central Intermountain (eastern AZ and CO) and southern Great Basin (southern NV) in the long term under

both low and high emission scenarios. This results might be related to by change in precipitation. Projected change in precipitation in this region is expected to be increase under climate change. Increased in precipitation are mostly to occur in winter while decreases or little change in precipitation is expected in this regions (Chambers and Pellant 2008).

Taken together, the projection results suggest that there is an association between climate change and forest productivity. This change in forest productivity varies across the regions and the scenarios. In the short term, high forest productivity is mostly projected in the Pacific west coastal and southern forest where ample forest productivity recorded in historical data has also been high. Forest productivity in these regions is projected to increase continuously in the long term and under all scenarios. Forest productivity in several parts of the North, the east central Intermountain, and the southern Great Basin is also projected to increase compared to its historical record but the changes would be small in the short term. However, the productivity in this region would strongly increase from mid-term (2030–2061) under the high emission scenario (RCP8.5) and high productivity would be expected in the long term and under all RCP scenarios. The productivity in the arid central Great Plains are would continue to be low in the short term under most climate scenarios. However, the productivity is projected to increase in the southern Great Plains while the northern Great Plains would continue to experience low productivity in the long term. This might be related to change in precipitation patterns in this region. Climate conditions are projected to become wetter in

the north while the southern part of the region is expected to become drier in the winter and spring in particular (Karl, Melillo, and Peterson 2009).

3.3 Conclusions

I have discussed the effects of CO_2 and climate variables on forest productivity across the continental U.S. using panel data analysis in this essay. Also, the impact of projected future climate change on forest productivity is investigated using the output from GCMs. In this essay regression results derived from both the linear and quadratic models are reported. The regression results indicate that there is a significant correlation between climate variables and forest productivity. Generally, forest productivity increases as temperature increases and precipitation decreases. Forest productivity positively respond to increasing spring, and fall temperature initially but at a decreasing rate. Increasing winter temperature have positive impact on forest productivity at an increasing rate. Tree density, CO_2 concentration in the atmosphere, and available water storage have a positive impact on forest productivity while soil draining class has a negative impact. Biomass initially has a positive impact on forest productivity at a decreasing rate. These relationships are significant at the 5% significance level. In the regression without quadratic precipitation and temperature terms, a significant ($p < 0.05$) positive correlation is found between fall precipitation, winter precipitation, fall temperature, winter temperature and forest productivity. Significant ($p < 0.05$) negative relationships are detected between summer precipitation, summer temperature, and forest productivity.

How future climate change will influence future forest productivity is projected. The projection results show that climate change would lead to higher future forest productivity in several regions including the South, the Pacific Coastal, the North, the northern Great Plains, the central Intermountain, and the southern Great Basin but forests in the southern Great Plains and northern Intermountain are projected to have low forest productivity. Especially, the difference between the southern Great Plain and other regions would be widened in the long term and under the higher GHG emission scenarios.

These results imply the possibility of an overall increase in forest productivity across the U.S. but the climate change will likely threaten the productivity in the southern Great Plains. This might be related to sharp change in precipitation in the region due to climate change. Given the uneven impacts of climate change on forest productivity, region-specific mitigation and adaptation strategies to climate change will be necessary, especially for the central region of the U.S.

The main contribution of this study is to investigate the climate change impact on forest productivity in the U.S. using a large-scale data on climate, forest, and soil. Especially, considering changes in CO_2 concentration pathways under different climate scenarios will help explore the potential future CO_2 impact on forest productivity in the global scheme. Many studies show that increasing CO_2 in the atmosphere will likely stimulate forest productivity if sufficient water and nutrients are available.

This study has some limitations. One source of limitation is that it does not consider several external variables besides climate, soil and forest characteristic. For example,

forest productivity is also possibly related to wildfire and insect outbreaks. Additionally, human activity such as urbanization and land use change can transfer forest type and quality, altering forest productivity. Further studies should explore the impact of these factors on forest productivity. Other limitation is that possible endogeneity problem is not considered in the empirical model. If biomass is part of average annual net growth (y_{it}), the error in y_{it} (ε_{it}) may be correlated with x_{it} (biomass). If the biomass is endogenous variable, the estimated coefficient could be biased because of $\text{cov}(x_{it,}\varepsilon_{it}) \neq 0$. To overcome this problem, some statistical tests such as Durbin-Wu-Hausman test should be performed in the future study. If endogeneity is detected, several alternative approaches such as instrument variables and Heckman selection correction could be considered. Another source of weakness in this study is assumption of constant coefficients in the projection procedure. More sophisticated projection strategy will be necessary to overcome this problem. Also, adding interaction terms among climate variables to a regression model should be considered to expand understanding of the relationship among the variables.

4. FOREST CARBON SEQUESTRATION AND OPTIMAL HARVESTING DECISION CONSIDERING SPB DISTURBANCE: A REAL OPTIONS APPROACH

Forest owners in the southern U.S. region are facing several risks and these risks are increasing in magnitude with climate change. Uncertainties associated with management decision are challengeable tasks of forest managers because inappropriate decision making can result in the loss of economic opportunities and profits. Moreover, the irreversible characteristic of forestry complicates the problems. For example, if forests have been cut, the opportunity of preserving them is lost (Conrad 2000) because it takes a long time for trees to regrow to their full size. Therefore, trade-offs between the social-economic benefit of harvesting timber and the ecological benefit of preserving the forests are a fundamental challenge for forest resource management decision making (Morgan, Abdallah, and Lasserre 2007). Moreover, as ongoing climate change tends to accelerate the uncertainties by altering forest disturbance and forest ecology. Therefore, examining strategic managerial decision making is paramount for forest owners to maximize their profit when they face uncertainties. To examine this need, this essay investigates a developed methodology to adopt for forest management strategy under uncertainties.

There are several techniques for analyzing the management of forest ecosystems, and one of the most widely used methods is calculating net present value (NPV) of forest using static discount rate. The main weakness with this approach is that it fails to take

into account the flexibility of harvest decisions due to timber price fluctuations because the NPV assumes a constant pattern of future cash flows (Tee et al. 2014). In addition, the linear and static nature of the NPV does not fully consider the possibility of reversible investment opportunities (Duku-Kaakyire and Nanang 2004). Therefore, the NPV method cannot appropriately evaluate the value of a forest owner's ability to change an initial strategy when future events become different from those initially predicted (Trigeorgis 1993).

To overcome this limitation, one of the alternatives is the real options technique. The definition of real option is the value of being able to choose some characteristic of decision allowing flexible outcome (Saphores and Carr 2000). The term "real" refers to tangible assets such as facilities and natural resource, rather than financial instruments such as foreign exchange and stock. The best way to measure social benefit is option pricing when there are uncertainties (Graham 1981) because option pricing can evaluate the social values of the project without knowledge of future events. The real options methodology provides an adequate framework for valuing the flexibility of decision making through including the risk and uncertainty incorporated with management decision making in option formulation (Dixit and Pindyck 1994).

Several studies have adapted a real options framework to the field of forestry. Developments real option study in forestry have increased the need for risk management to forest investment and forest business management for optimizing the financial performance of forest assets. Among the early authors who introduced the real options framework into forestry are Miller and Voltaire (1983). They examined the solution to

the rotation problem using a stochastic model. Brazee and Mendelsohn (1988) found that allowing for flexible harvest decisions can increase the net present value of expected return compared to traditional NPV approach under fixed harvest decision. Plantinga (1998) highlighted the role of option values in the optimal timing of harvests. He investigated that the option value is a premium over the expected net present value of a timber stand reflecting the opportunity cost of delaying harvesting until appropriate future stand value is revealed. Duku-Kaakyrie and Nanang (2004) compared forest investment values derived from the Faustmann NPV model and a real options model using the binomial tree method. Their study included four option strategies: to delay harvest, to expand planting size, to abandon harvest if timber prices decrease below a certain threshold, and one includes all the three above options. They found that forest flexible harvest decision (real option) add forest investment values. Especially, expanding planting size adds more value to the investment project among four option strategies. Morck, Schwartz, and Stangeland (1989) valued the forest resources as a function of stochastic price and inventory, and optimal production policy using a contingent claims approach. However, a limitation of their study is an assumption of geometric Brownian motion for timber price. An assumption of geometric Brownian motion is not realistic because the geometric Brownian motion assumes continuously rising expected price and variance over time without bounds (Insley and Rollins 2003). Unlike Morck et al. (1989), Haight and Holmes (2011), Gong and Yin (2004), and Newman and Yin (1996) showed that competitively determined timber price in the markets followed autoregressive (mean reverting) process rather than geometric

Brownian motion. Guthrie (2009) applied the binomial tree method to calculate the optimal harvest decision under a flexible harvest decision framework (real options). This approach is advantageous in that it is relatively easy and intuitively understandable.

Currently, many of studies have attempted to incorporate of ecosystem service such as carbon sequestration into the real option analysis. Since the CO_2 concentration in the atmosphere is treated as main source of global climate change, the social costs of climate change would become enormous. Forests play a significant role in carbon sequestration because trees absorb carbon during growth. Several studies (Alavalapati and Kant 2014; Tee et al. 2014; Petrasek and Perez-Garcia 2010) have asserted that we should consider forests not only as a source of timber but also a carbon pool. Therefore, the ability of forests for carbon sequestration should be included when we evaluate the forest values. The real option approach is very useful in understanding tradeoffs between timber and ecosystem services provided by forests to incorporate uncertainties and flexibility in timing (Alavalapati and Kant 2014). Petrasek and Perez-Garcia (2010) determined optimal harvest schedule including revenues from carbon trading in a real option model. Romero et al. (1998) examined an approach for the determination of optimal forest rotation considering both timber production and carbon sequestration for the climate change mitigation purpose. Tee et al. (2014) applied real options analysis to forestry carbon valuation under the New Zealand emission trading scheme. They incorporated both stochastic timber price and carbon value into calculating real option value of the New Zealand forests using the binomial tree method. However, most of the analyses so far only consider carbon sequestration in live standing trees. Damaged trees represent a

substantial proportion of the total carbon sink/source in forest stands, and these damaged trees will affect tree management decision such as harvesting age (Asante, Armstrong, and Adamowicz 2011). One of the main causes of tree damages in the southern U.S. is southern pine beetle (SPB) infestation (Preisler et al. 2012). Trees damaged by SPB will affect the amount of total carbon sequestration and the forestland value. Moreover, the forest owner's decision will be affected because of the changing forest value due to SPB damages.

The utility of the real options valuation approach to the field of forest management decision making considering various cases that forest owners might face is demonstrated in this essay. The term "valuation" means the value of bareland where loblolly pine, *Pinus taeda*, is planted. Loblolly pine is the most commercially important forest species in the southern U.S., and its native range extends throughout 14 states form southern New Jersey to central Florida and to eastern Texas (Baker and Langdon 1990). The objectives of the study are to find answers to the following questions:

1) How does the sawtimber price volatility affect the bareland valuation of loblolly pine forests in the southern U.S.?
2) How much could the bareland value be changed if we consider not only timber price but also the carbon sequestration ability of the forest and pine beetle outbreak risk?
3) What is the optimal harvesting decision for loblolly pine plantations in the southern U.S. considering timber price volatility, carbon value, and pine beetle infestation risk?

Three general approaches are used to implement real option valuation including partial differential equation, simulation and binomial trees (Tee et al. 2014). Among the three approaches, binomial approach to calculate real option value is applied in this essay because the binomial tree is numerically efficient and conceptually undemanding technique to calculate option value. Also, the binomial tree approach is the computational ease and intuitively understandable when calculate the early exercise premium present in options (Mastro 2013). The binomial tree method developed by Guthrie (2009) is useful to calculate the valuation of flexible rotations; as such, the Guthrie's approach for evaluating option value is used.

The main contribution of this study is to evaluate the optimal stand management decision considering timber price, carbon sequestration, and trees damaged by SPB. There are many studies that evaluate the value of the forests using the real options theory but researchers have not treated damaged trees in detail. Insect infestation directly affects forest owner's profit because it reduces timber productivity. In terms of forest carbon sequestration, dead trees do not release large amounts of CO_2 into the atmosphere than expected because dead trees hold their carbon for a long time and prevent it from quickly being released into the atmosphere (Moore et al. 2013). Without considering this, the carbon sequestration ability of forest could be underestimated. This essay provides guidelines for forest owners for improving their timber harvest decisions to consider some cases they could face under climate change including timber price volatility risk, benefit from mitigation CO_2 due to forest carbon sequestration, and SPB outbreak risk.

4.1 Model setting up

4.1.1 Binomial tree of price movement

Timber price volatility is one of the critical uncertainties that forestland owners could face. Assume that a forestland owner is confronted with the timber price risk. Suppose that $X(0,0)$ is the current price of sawtimber (\$/m^3). $X(i,n)$ denotes the sawtimber price at the node (i, n), where i is the number of downward price moves and n is the time step. Sawtimber price can move upwards with probability $\theta_U(i,n)$, and can move downwards with probability $\theta_D(i,n)$. Suppose that U, D are the size of up move and down movement where $U = e^{\hat{\sigma}\sqrt{\Delta tm}}$ and $D = e^{-\hat{\sigma}\sqrt{\Delta tm}}$, respectively. Sawtimber could be either increased or decreased with probability $\theta_U(i,n)$ or $\theta_D(i,n)$ at each node. If sawtimber will be increased at the node (i, n+1), the sawtimber could be $X(i,n+1) = X(i,n)U$ and the sawtimber could be $X(i+1,n+1) = X(i,n)D$ when sawtimber will be decreased. The binomial tree of sawtimber price movement process for n = 2 is described in Figure 5.

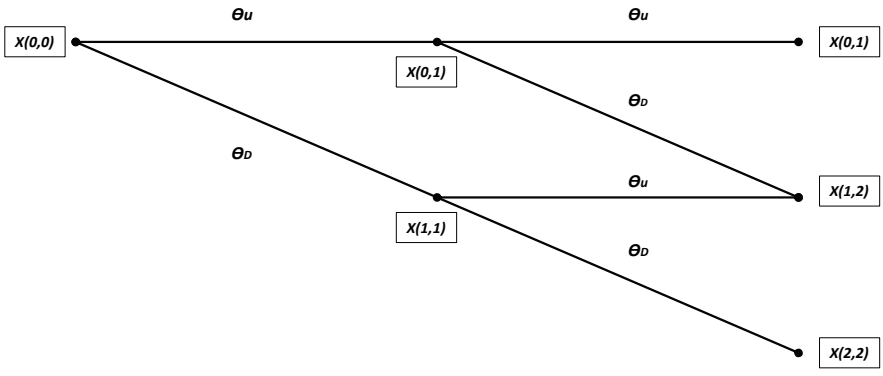


Figure 5 Two-step price binomial tree

The forestland owners expect some profits from the sales of forest products; the amount of the profit depends on the timber price movement in the market. Assume that this timber price follows a mean-reverting series. Schwartz (1997) suggested strong mean reversion in the commercial commodity prices. The mean-reverting price process implies that unlike the random walk price process, shocks to mean-reverting timber spot prices are not permanent. In other words, sudden increase in timber price leads to an increase in supply as well so the market price of timber will move back towards the timber's long-run marginal cost of production in long-term. Likewise, a sudden decrease in timber price causes a reduction in supply that triggers increase in future timber price. Therefore, a sudden increase (decrease) in timber spot price is not long lasting (Guthrie 2009).

Under the mean-reverting price assumption, the logarithm of the price follows a mean reverting process (first order autoregressive):

(14)
$$P_{j+1} - P_j = \alpha_0 + \alpha_1 P_j + u_{j+1}$$
$$u_{j+1} \sim N(0, \phi^2)$$

where p_j is the market price of sawtimber, u_j is the error term that follows normal a distribution with mean=0 and variance= ϕ^2. After obtaining OLS estimated coefficients, $\hat{\alpha}_0$, $\hat{\alpha}_1$, and $\hat{\phi}^2$, from equation (14), we can calculate Ornstein-Uhlenbeck parameters with the following equation using the OLS coefficients:

(15)
$$\hat{a} = \frac{-\log(1+\hat{\alpha}_1)}{\Delta t_d}, \quad \hat{b} = \frac{-\hat{\alpha}_0}{\hat{\alpha}_1}, \quad \hat{\sigma} = \hat{\phi}\left(\frac{2\log(1+\hat{\alpha}_1)}{\hat{\alpha}_1(2+\hat{\alpha}_1)\Delta t_d}\right)^{1/2}$$

Where a = mean reversion rate, b = long-term level price, σ = volatility of the Ornstein-Uhlenbeck parameters, and Δt = size of time step. From the solution to equation (15), the binomial tree parameters, U, D, and $\theta_U(i,n)$ are calculated by the following equations:

(16) $U = e^{\hat{\sigma}\sqrt{\Delta tm}}$, $D = e^{-\hat{\sigma}\sqrt{\Delta tm}}$,

$$\theta_u(i,n) = \begin{cases} 0 & \text{if } \frac{1}{2} + \frac{(1-e^{-\hat{a}\Delta tm})(\hat{b} - \log(X(i,n))}{2\hat{\sigma}\sqrt{\Delta t_m}} \le 0 \\ \frac{1}{2} + \frac{(1-e^{-\hat{a}\Delta tm})(\hat{b} - \log(X(i,n))}{2\hat{\sigma}\sqrt{\Delta t_m}} & \text{if } 0 < \frac{1}{2} + \frac{(1-e^{-\hat{a}\Delta tm})(\hat{b} - \log(X(i,n))}{2\hat{\sigma}\sqrt{\Delta t_m}} < 1 \\ 1 & \text{if } \frac{1}{2} + \frac{(1-e^{-\hat{a}\Delta tm})(\hat{b} - \log(X(i,n))}{2\hat{\sigma}\sqrt{\Delta t_m}} \ge 1 \end{cases}.$$

4.1.2 Calculating risk neutral probability using capital asset pricing model (CAPM)

The risk neutral probability is probability of future outcome under the assumption that underlying risk asset has the same expected return as riskless assets such as Treasuries bills (Hull 2008). Capital Asset Pricing Model (CAPM) can be applied to calculate the risk neutral probability. The risk neutral probability Π_U is calculated by subtracting a Market Risk Premium adjustment (MRP_{adj}) from the valuation binomial tree's probability θ_U (Guthrie 2009):

(17)
$$\Pi_U = \theta_U - MRP_{adj}, \text{ and}$$
$$\Pi_D = 1 - \Pi_U.$$

The MRP_{adj} is obtained by regressing returns on the market portfolio (Guthrie 2009) . The common stock indices such as S&P 500 and NASDAQ are widely used as a proxy

for the market portfolio. This study uses the S&P 500 index as a proxy of the market portfolio.

4.1.3 Binomial tree of valuation movement

The forest value in each node is denoted by $V(i,n)$, and $V(i,n)$ is related to timber price movements $\theta_U(i,n)$ and $\theta_D(i,n)$. The two-step valuation binomial tree (n=2) is shown in Figure 6. The forest value could be increased with probability $\theta_U(i,n)$ or decreased with probability $\theta_D(i,n)$. n is time steps and i is the number of down movements.

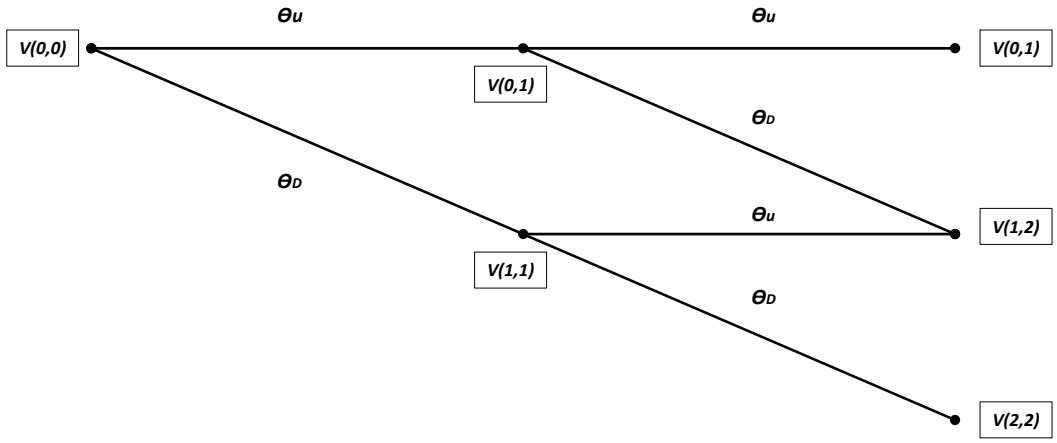


Figure 6 Two-step valuation binomial tree

Because the risk neutral probability can be expressed as $\Pi_U = \theta_U - MRP_{adj}$ and $\Pi_D = 1 - \Pi_U$, the two-step valuation binomial tree with risk neutral probability is shown in Figure 7.

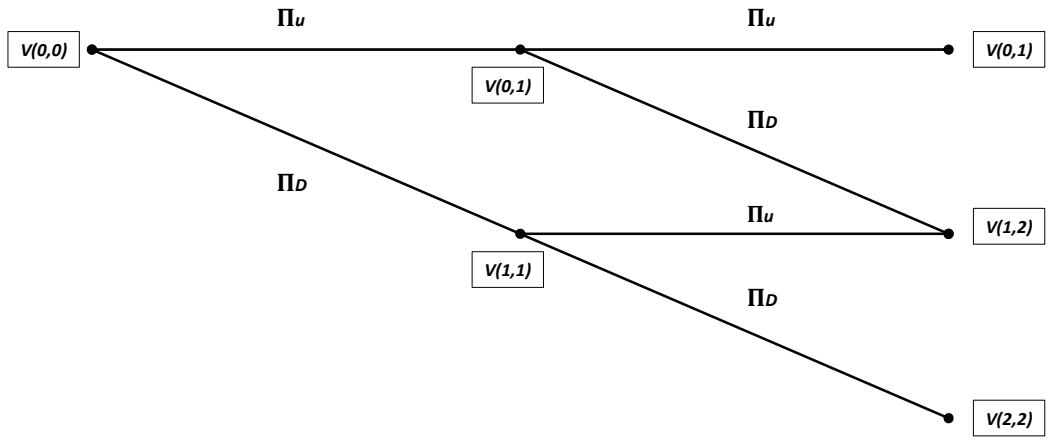


Figure 7 Two-step valuation binomial tree with risk neutral probability

The valuation binomial tree is calculated backwards starting from $V(i,N)$ where N denotes the terminal time step and the ending is $V(0,0)$. Therefore, valuation at node $V(i,n)$ is

(18) $$V(i,n) = \frac{\Pi_U V(i,n+1)}{R_f} + \frac{\Pi_D V(i+1,n+1)}{R_f},$$

where R_f = (1+discount rate).

At node (i,n), the forestland owner faces two alternative situations. The first alternative is harvesting. If she/he decides to harvest the forest, she/he must pay harvest

costs H per timber volume. Total costs are equal to $HQ(n)$ where $Q(n)$ is the total volume of timber harvested. She/he gains some revenue from selling the timber, which is equal to $X(i,n)\mathrm{Q(n)}$, where $X(i,n)$ indicates the market timber price in the n th time period. B is the bareland value after harvest. After harvest, the forestland is turning into bareland worth B per hectare. She/he also must pay taxes at a tax rate of T. All in all, the harvest payoff equation is

$$(1-T)(X(i,n)-H)Q(n)+B. \tag{19}$$

The second alternative is that the forestland owner decides not to harvest, rather postpone the harvest until an appropriate timber price is going to be reached. In this case, she/he must pay forest maintenance cost per hectare. After one period, the timber price is going to move either up and down. So the corresponding forest value is either $V(i,n+1)$ or $V(i+1,n+1)$. Thus, the expected payoff from postponing harvest is

$$-(1-T)\mathrm{C}+\frac{\Pi_u(i,n)V(i,n+1)+\Pi_d(i,n)V(i+1,n+1)}{R_f} \tag{20}$$

for all $n=N-1$ where N is the terminal node and C is the forest maintain cost. The payoff at the terminal node is

$$(1-T)(X(i,N)-H)Q(N)+B. \tag{21}$$

At each node, the decision to harvest or not harvest is re-evaluated. If the present value of the cash flows from harvesting is larger than the present value of the cash flows from not harvesting at the node, the optimal decision is to harvest at this node. On the other hand, if the present value of the cash flows from not harvesting is larger than the present

value of the cash flows from harvesting, the optimal decision is not harvesting at this node. Therefore, the valuation at each node $V(i,n)$ is

$$V(i,n) = \max \begin{Bmatrix} (1-T)((X(i,n)-H)Q(n)) + B, \\ -(1-T)M_T + \dfrac{\Pi_u(i,n)V(i,n+1) + \Pi_d(i,n)V(i+1,n+1)}{R_f} \end{Bmatrix}. \quad (22)$$

The first line in the max function, equation (22), implies the cash flow from harvesting. On the other hand, the second line represents the cash flow from not harvesting. The forest owner makes a decision by comparing the present values of the corresponding expected future cash flows at every node. This problem is solved by calculating $V(i,n)$ backwards, starting from the terminal node where $n = N$ and ending at $V(0,0)$.

4.1.4 Market value of bareland

The backward procedure is conducted recursively over multiple iterations and each iteration represents one harvest/planting rotation. Calculating the market value of bareland follows these steps: (1) The bareland value is zero when calculating value for the first iteration. (2) After finishing first iteration, $V(0,0)$ (The market value of the forest at date 0) is obtained. (3) The bareland value is estimated by $B = V(0,0) - (1-T)G$ which implies $V(0,0)$ minus the cost of replanting the forest. This first iteration bareland value implies real option value for a single rotation (the value for single rotation forest with flexibility). When calculating the value of the second iteration, the bareland value derived from the first iteration is used as the new initial value instead of 0. This process is repeated until the bareland values converge. This

converged bareland value is the real option value with infinite rotation (value of an infinite rotation forest with flexible harvest).

4.1.5 Value of flexibility

The value of flexibility is calculated by comparing bareland value from fixed harvest with the value of real option. The valuation method for fixed harvest follows the same process with real option but assumes the harvest date is fixed. Suppose that the harvest decision is fixed at node *M* (e.g., 30 years or any years smaller than the terminal node *N, M*<*N*), the terminal condition is $(1-T)(X(i,M)-H)Q(M)+B$ and the years larger than *M* are ignored. The terminal condition is still not different from that used in the real option method except *M* instead of *N* is used. However, at all nodes earlier than *M,* there is no reevaluation of the decision since the harvest date is fixed. Therefore, the decision to "wait" is only at nodes *n*<*M* and the recursive equation at nodes *n = (M-1)* to *n*=0 becomes

(23) $$V(i,n) = -(1-T)M_T + \frac{\Pi_u(i,n)V(i,n+1) + \Pi_d(i,n)V(i+1,n+1)}{R_f}$$

The value of bareland converges to the value under the infinite rotation after certain number of iterations. This value is Land Expectation Value (LEV) of infinite rotation (Tee et al. 2014). The difference between LEV and real option (flexible harvest decision) value is the value of flexibility.

4.2 Application of real option to flexible harvest decision

Forests absorb CO_2 from the atmosphere through photosynthesis (IPCC 2000b). Therefore, the stock of stored carbon in trees should be considered when we choose the optimal harvest age. Many studies have examined the relationship between optimal harvest age and carbon storage ability of standing trees, but most analyses have focused on carbon sequestration only in living trees. Dead trees, however, represent a crucial proportion of the total carbon stored in a forest (Asante and Armstrong 2012). Therefore, stored carbon by dead trees may be important when determining optimal harvest age. This study aims to establish three different real options models to compare optimal harvest ages and bareland prices.

4.2.1 Timber only

The valuation function for timber only is the same as equation (22) discussed in the previous section:

(24) $$V(i,n)=\max\left\{\begin{array}{l}(1-T)((X(i,n)-H)Q(n))+B,\\ -(1-T)M_T+\dfrac{\Pi_u(i,n)V(i,n+1)+\Pi_d(i,n)V(i+1,n+1)}{R_f}\end{array}\right\}.$$

4.2.2 Timber and carbon storage in living trees

Carbon of trees provides additional benefit to forest owners. Carbon benefits are usually considered the amount of carbon per unit volume of biomass (Amacher, Ollikainen, and Koskela 2009). I denote $Q(n)$ as a growth function of a forest at time n and Q_c as the carbon stock (t/ha) in the forest of volume $Q(n)$. Therefore, the change in

the benefit from sequestrated carbon in living trees is a function of time n : $X_s([Q_c(n)-Q_c(n-1)])$ where X_s is the social cost of carbon. The stored carbon in standing living trees are derived from a forest ecosystem yield table. The forest ecosystem yield table (Smith et al. 2006) provides tabulated carbon density at different stand age and timber volume. The, the real option valuation function for carbon sequestration by trees is:

(25)
$$V(i,n)=\max\begin{Bmatrix}(1-T)\{(X(i,n)-H)Q(n)-\mathrm{X}_s\,Q_c(n-1)\}+B,\\ -(1-T)(-M_T+X_s[Q_c(n)-Q_c(n-1)])\\ +\dfrac{\Pi_u(i,n)V(i,n+1)+\Pi_d(i,n)V(i+1,n+1)}{R_f}\end{Bmatrix}.$$

4.2.3 Timber and carbon storage in living trees and dead trees damaged by SPB

The SPB infestation risk affects both the amount of carbon sequestration in trees and timber/wood products per unit forest land area. The trees killed by SPB have a lower merchantable value and carbon storage than healthy trees, but these dead trees still represent a substantial proportion of the total carbon stored in forest stands (Asante and Armstrong 2012) and can/will be replaced by new trees naturally and with human assistance. Assume that the percent of trees killed by SPB in each year is given by δ%, the forest owners may clear cut damaged trees in the same year or delay the harvest to a future year. In this case, one should separate two carbon sequestration pools: 1) carbon pool from live standing trees, and 2) carbon pool from trees killed by SPB.

The timber production in year n will decrease due to SPB damage. Assume that average yearly SPB damage is given by δ%, the total timber production (m^3/ha) in year n will decrease according to equation (26). Therefore, the total tree production will be $Q^*(n)$ instead of $Q(n)$ as the following:

$$Q^*(n) = Q(n) - \delta Q(n). \tag{26}$$

The value of the live standing tree pool is

$$X_s\left[Q_c^*(n) - Q_c^*(n-1)\right]. \tag{27}$$

Equation (27) implies the value of carbon stored in live standing trees in each year. $[Q_c^*(n) - Q_c^*(n-1)]$ is carbon density (t/ha) and X_s is the social cost of carbon ($/t). The carbon storage of live trees can be calculated by using the "forest ecosystem yield table" from USDA Forest Service. The forest ecosystem yield table (Smith et al. 2006) provides tabulated carbon density at different stand ages and timber volumes by carbon pools including live trees, standing dead trees, soil organic matters and so on. If timber age or volume is not explicitly provided on a table, the carbon stock is estimated using an interpolation method. Assume that average yearly SPB damage is given by δ%, the total volume of live trees on the site in year n is $Q^*(n) = Q(n) - \delta Q(n)$. Therefore, the carbon density stored in live trees, $Q_c^*(n)$ is calculated from the forest ecosystem yield table with the corresponding volume $Q^*(n)$ using an interpolation method.

The damaged tree pool (DTP) implies carbon stored in standing dead trees killed by SPB. The trees killed by SPB are assumed to decompose at a rate of η per year, and

trees killed by SPB are added to the DTP each year. Therefore, the DTP pool grows according to

(28) $$D(n+1) = (1-\eta)D(n) + \delta Q(\text{n+1}).$$

where $D(n)$ represents carbon stored in the damaged tree pool. The estimated decomposition rate is η =0.00578, which is derived from Asante, Armstrong, and Adamowicz (2011). δ is be average SPB risk. The change in DTP for the no harvest case is $\Delta D(n) = -\eta D_n + \delta Q(n)$, which implies $\Delta D(n) = -\eta e^{n\eta}(D(0) + \sum_0^n e^{r\eta} Q(n-1))$ $+\delta Q(n)$ where r = the discount factor. Combining all equations above yields the real options value function under SPB risk:

(29) $$V(i,n) = \max \left\{ \begin{array}{l} (1-T)\{(X(i,n)-H)Q^*(n) - \mathrm{X}_s[Q_c^*(n-1) + \mathrm{D(n-1)}]\} + B, \\ -(1-T)(-M_T + X_s([Q_c^*(n) - Q_c^*(n-1)] + \Delta D(n))) \\ + \dfrac{\Pi_u(i,n)V(i,n+1) + \Pi_d(i,n)V(i+1,n+1)}{R_f} \end{array} \right\}.$$

Because the SPB risk δ is assumed to be constant, sensitive analysis is performed. (Starkey et al. 1997) examined that at least 10 percent of the slash and/or loblolly pine forest was infected by SPB in southern U.S. Reed (1979) simulated the spread of SPB infestation using a nonlinear spot growth model. He tested the model on 11 infestation spots from northern Georgia and projected 6% of total number of tree killed by SPB. However, it was not very precise model to estimate damages from individual infestation (Thatcher 1981). There are not many studies to investigate the SPB infestation in loblolly pine forest only and previous studies cannot reflect the current trend of SPB

infestation in loblolly pine forest. With this limitation, this essay assumes 3% of SPB damages. This number may reflect the current overall trend of SPB infestation risk in the southern U.S.

4.3 Data and cash flows

4.3.1 Timber volume and mean carbon stock in the South and South Central region

The mean volume of timber growth and estimated carbon stock for loblolly pine in the southern U.S. are shown in Figure 8 and Figure 9, respectively. The mean volume of timber growth and estimated forest carbon stock of southern (or loblolly) pines are obtained from "Forest Ecosystem Carbon Tables" from USDA Forest Service (Smith et al. 2006). The Tables provide the estimated mean volume of timber and corresponding carbon stock for common forest types in each of U.S. region. The Tables were developed using a national-level forest carbon accounting model (FORCARB2), a timber projection model (ATLAS), and USDA Forest Service, Forest Inventory and Analysis (FIA) Program's database of forest survey(FIADB) (Smith et al. 2006).

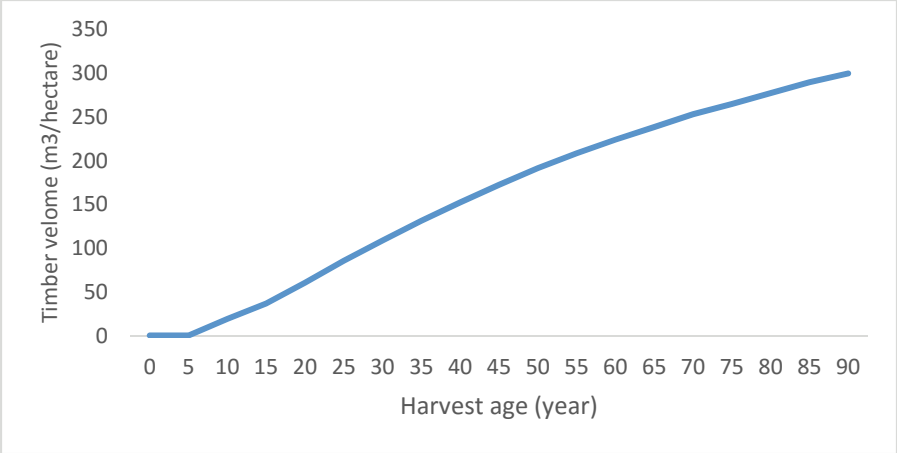


Figure 8 Estimates of timber volume for loblolly pine stands in southern U.S.

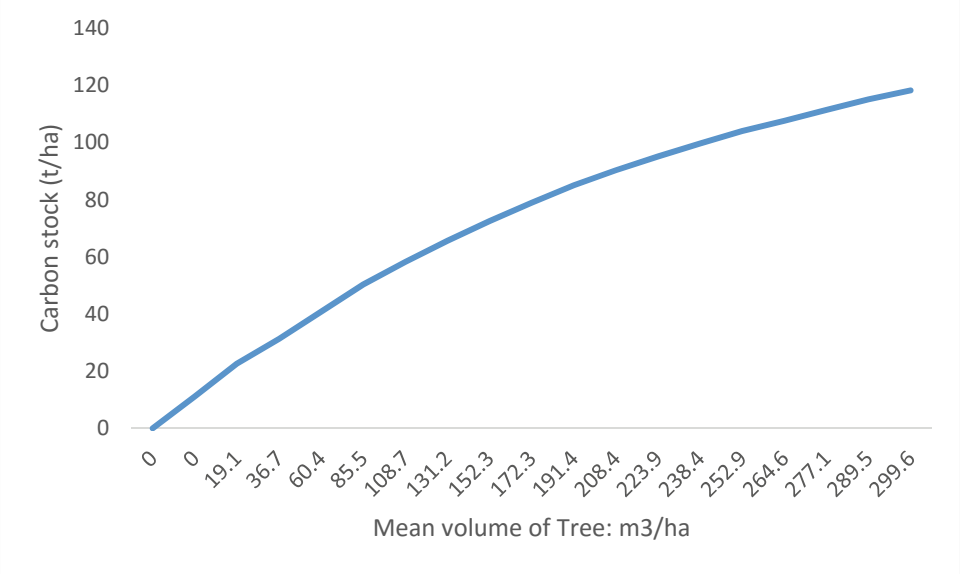


Figure 9 Estimates of carbon stock for loblolly pine stands in southern U.S.

4.3.2 Costs and cash flows

Forest management costs and cost cash flows are shown in Tables 12 and 13. These costs are based on market research (Doran et al. 2009).

Table 12 Forest management costs

Management cost description	Cost ($)
Regeneration cost (including the cost of site preparation, seedling, planting and weed control), G	\$618/ha
Forest management cost, M_T	\$22/ha
Tax rate, T	28%
Harvest cost, H	\$68.67/m^3
Discount factor (Risk free interest rate base on current 20 year U.S. treasury rate), r	2.5%

Table 13 Cost cash flow

Year	0	1	…	15th rotation	…	24th rotation	…	90th rotation
Planting Cost	(618)	(618)	…	(618)	…	(618)	…	(618)
Maintenance Cost, M_T	(22)	(22)	…	(22)	…	(22)	…	(22)
Timber Revenue	\$	\$	…	\$	…	\$	…	\$
Harvest Cost	\$	\$	…	\$	…	\$	…	\$

Carbon stocks are calculated based on the timber volume for the loblolly pine forest (living and dead trees, m^3/ha) using the forest carbon table in "Methods for Calculating Forest Ecosystem and Harvested Carbon with Standard Estimates for Forest Types of the United States" (Smith et al. 2006). Average stumpage prices for sawtimber sold by National Forests, arranged by selected species, 1965–2012 (Figure 10) are used. Using equation (15) and a mean reverting timber price assumption, the Ornstein-Uhlenbeck parameters with $\hat{a} = 0.074$, $\hat{b} = 0.42$, and $\hat{\sigma} = 0.15$. Using these parameters, the

estimated long run timber price is $\exp(\hat{b})$ = \$136.88/m^3, and upward and downward movement factors are U =1.16 and D = 0.87. The market risk premium is assumed as 3.5% and estimated market risk premium adjustment (MRPA) from regression of price changes on stock market return (S&P 500) is 0.027. Based on these values, the risk-neutral probability of an up or down movement (Π_U or Π_D) are calculated.

The average stumpage price of southern pine sawtimber price movement is shown in Figure 10. \$150 is long - term level price of southern pine sawtimber stumpage price calculated by equation (15). The timber stumpage price is an ideal state variable for calculating forest value because the timber stumpage price is price of timber while it is still standing so the stumpage price does not reflect additional cost such as cost of harvesting and transporting log to mill (Guthrie 2009). The social costs of carbon (Figure 11) used in the model are obtained from the Interagency Working Group's Technical Support Report (Interagency Working Group 2013).

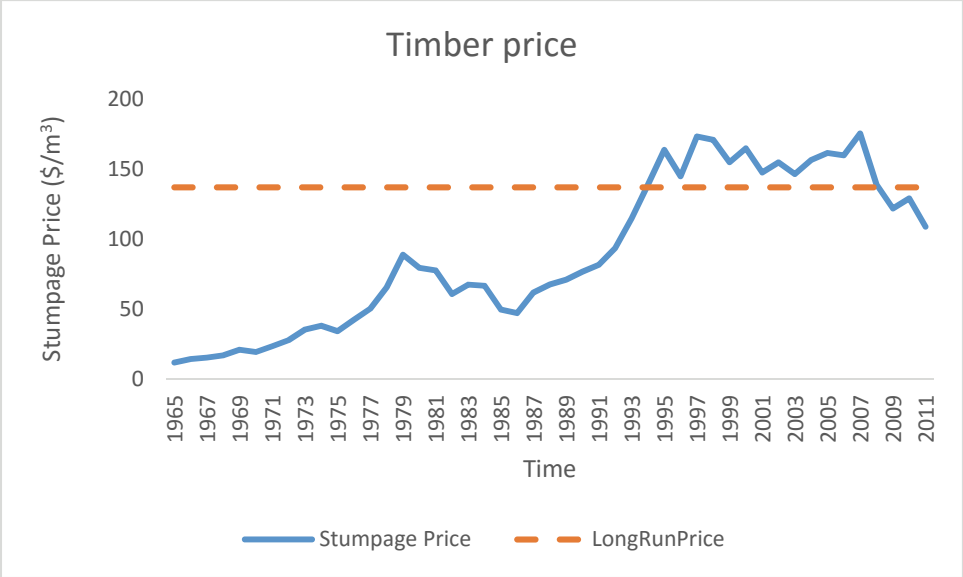


Figure 10 Average stumpage price of sawtimber (Source: Howard and Westby 2013)

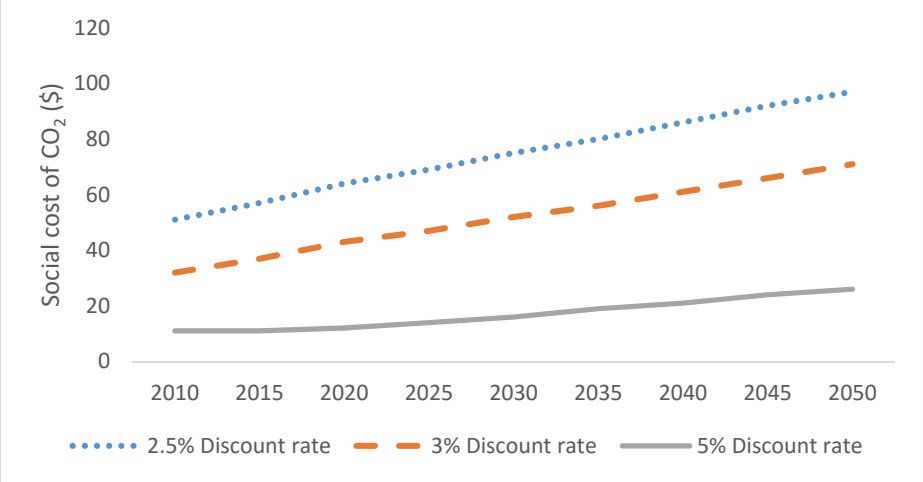


Figure 11 Revised social cost of CO_2, 2010–2050 (in 2007 dollars per metric ton of CO_2) (Source: Interagency Working Group 2013)

4.4 Results

4.4.1 Land value (real option), harvest threshold and value of flexibility

The results for the flexible harvest (real option) of infinite rotation. For the timber only cases, the bareland value converges to $5329/ha, after nine cycles/rotations of harvest-and-replant are shown in Figure 12. For the timber plus carbon case ($75/of carbon cost is assumed), the bareland value converges to $7408/ha, after eight cycles of harvest-and-replant. For the case considering damage of SPB case (a 3% of SPB damaged is assumed), the bareland value converges to $6918/ha, also after eight cycles of harvest-and-replant. To consider the carbon storage ability of forest, the forest value would increase by 39%, compared to the case of considering only timber price. The SPB risk would decrease the forest value. The bareland value damaged by SPB would decrease by 6% compared to the case of the timber plus carbon forest. However, the SPB damaged forest has a higher value than the timber only case because even if the forest is damaged by SPB, the forest still has the ability of carbon storage. Thus, the value of carbon storage would compensate the price loss from damaged timber by SPB.

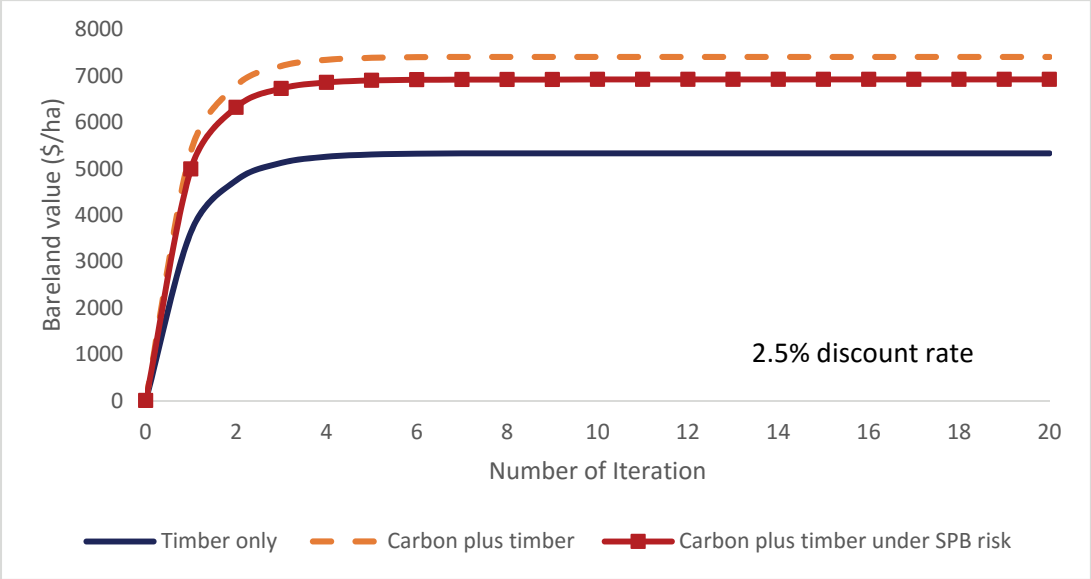


Figure 12 Infinite rotation values for bareland :

The results for the flexible harvest (real option) of infinite rotation. For the timber only cases, the bareland value converges to $5329/ha, after nine cycles/rotations of harvest-and-replant are shown in Figure 12. For the timber plus carbon case ($75/of carbon cost is assumed), the bareland value converges to $7408/ha, after eight cycles of harvest-and-replant. For the case considering damage of SPB case (a 3% of SPB damaged is assumed), the bareland value converges to $6918/ha, also after eight cycles of harvest-and-replant. To consider the carbon storage ability of forest, the forest value would increase by 39%, compared to the case of considering only timber price. The SPB risk would decrease the forest value. The bareland value damaged by SPB would decrease by 6% compared to the case of the timber plus carbon forest. However, the SPB damaged forest has a higher value than the timber only case because even if the forest is

damaged by SPB, the forest still has the ability of carbon storage. Thus, the value of carbon storage would compensate the price loss from damaged timber by SPB.

The market value of forests for fixed harvest of infinite rotation in Figure 13. The infinite rotation problem is commonly known as the Faustmann rotation, which is defined "choosing the harvest period to maximize the net present value of a series of future harvest" (Grafton et al. 2008, 138; Gane, Gehren, and Faustmann 1968). In his study, the NPV of a forest could be indicated as a sum of discount net cash flow over an infinite time horizon (Viitala 2006). For evaluating the value of forests for fixed harvest, the same process is used with flexible harvest but the fixed harvest case assumes the harvest decision is fixed at the node t = fixed harvest age. Thus, the backward evaluations are started from node t (e.g., 60 years, 50 years) rather than N, without no re-evaluation of a harvest decision. Thus, the valuation equation for each node is

$$V(i,n) = -(1-T)M_T + \frac{\Pi_u(i,n)V(i,n+1) + \Pi_d(i,n)V(i+1,n+1)}{R_f}. \tag{28}$$

The value of bareland converges to infinite rotation NPV of fixed harvest.

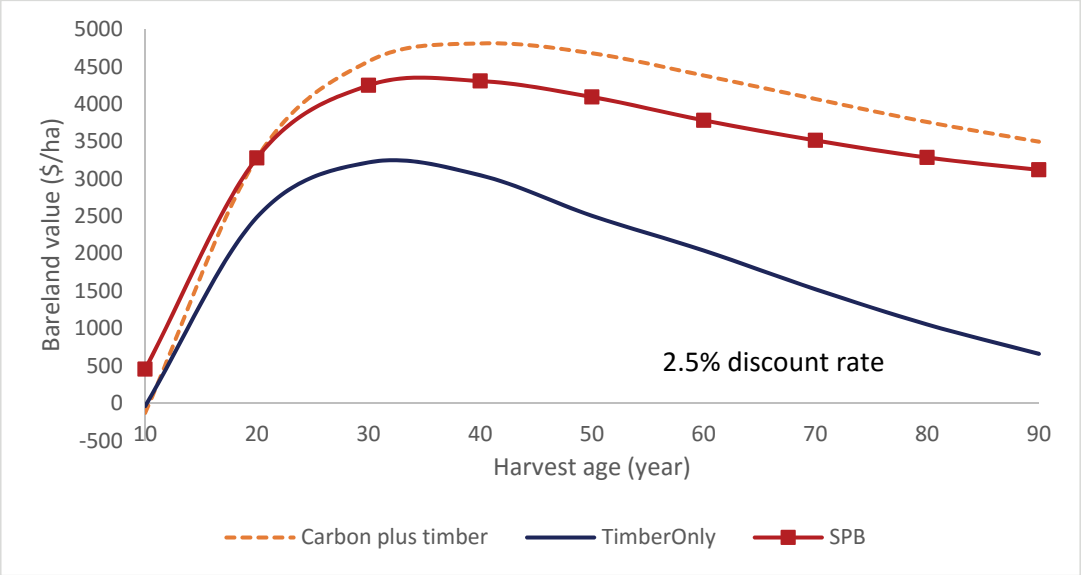


Figure 13 Market value of bareland (fixed harvest, infinite rotation)

In contrast to the real option case, fixed harvest age is assumed. In the timber only case, the net present value (NPV) of the forest is the highest, $3220/ha, around age 30. In timber plus carbon case, the net present value of forest is at its maximum, $4812/ha, at age 40. In the case of timber plus carbon under SPB risk, the net present value of the forest is the highest, $4308/ha, at age 40. If allowed for flexible harvest (real option), the market value of the bare land is $5329/ha for the timber only case, $7408/ha for the timber plus carbon case, and $6918/ha for the case of timber plus carbon under SPB risk, respectively. Thus, timber harvest flexibility adds approximately 65% to the value of bareland for the timber only case (54% for the timber plus carbon case, 61% for the case of timber plus carbon under SPB risk). This result shows that flexible harvest generates the higher valuation through allowing forest owners to make a better investment decision

using information of various price levels. If timer prices are low, the forest owners can postpone harvest while they hasten harvest when prices are high.

Using these results, we can estimate the optimal harvest/rotation age as well. The NPV of the forest is maximized at the point of optimal rotation age both fixed rotation and infinite rotation. The optimal rotation age is 30 years for the timber only case, 40 years for the timber plus carbon case and 40 years for the case of timber plus carbon forest under SPB risk. The optimal rotation age increases when considering the carbon storage ability of the forest. In the case of SPB damage, the optimal rotation is similar to the carbon forest case, but the forest value is lower than that under the carbon forest case at the optimal rotation age. The value of flexibility also increased if we consider carbon storage ability of the forest because capacity to be flexible can increase the value of investment when uncertainty and irreversibility become larger (Tee et al. 2014).

Figures 14–16 show the optimal harvest threshold for infinite rotations, timber only case, carbon plus timber case and carbon plus timber under SPB risk. The values are rounded off to the nearest whole number. These figures show the harvest threshold price for all possible ages of the forest. The shaded area implies the range of sawtimber price that is optimal to harvest for a given forest age. In every case, if the forest is very young, the threshold price is high so the optimal choice is not to harvest. However, as the age of the forest increases, the threshold price falls. For example, in Figure 14, if the timber price is above \$258/m^3 at forest age between 20 to 26 years old, the optimal decision is harvest while the optimal decision would be deferring harvest if the timber price is below \$258/m^3 at forest age between 20 to 26 years.

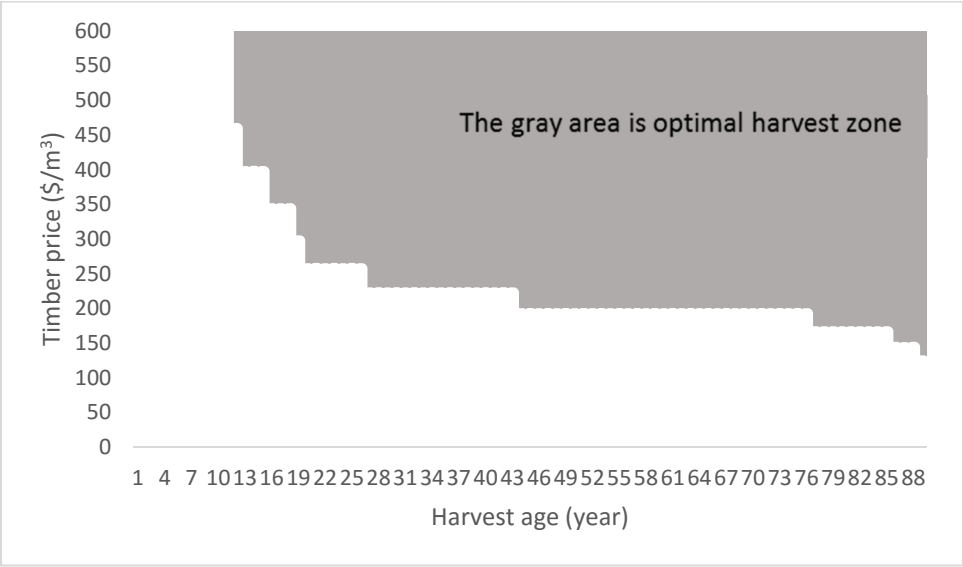


Figure 14 Sawtimber threshold prices for the timber-only case

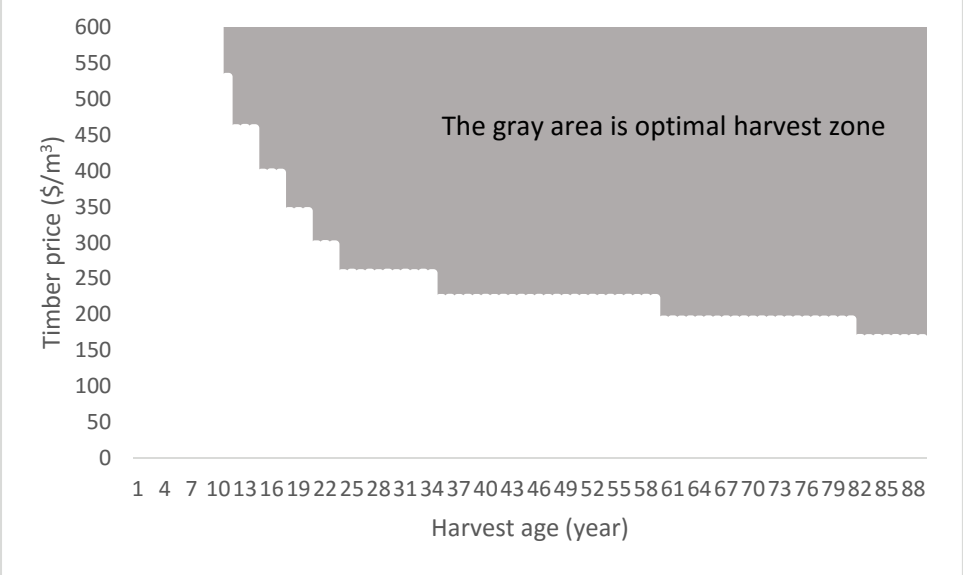


Figure 15 Sawtimber threshold prices for the carbon-forest case

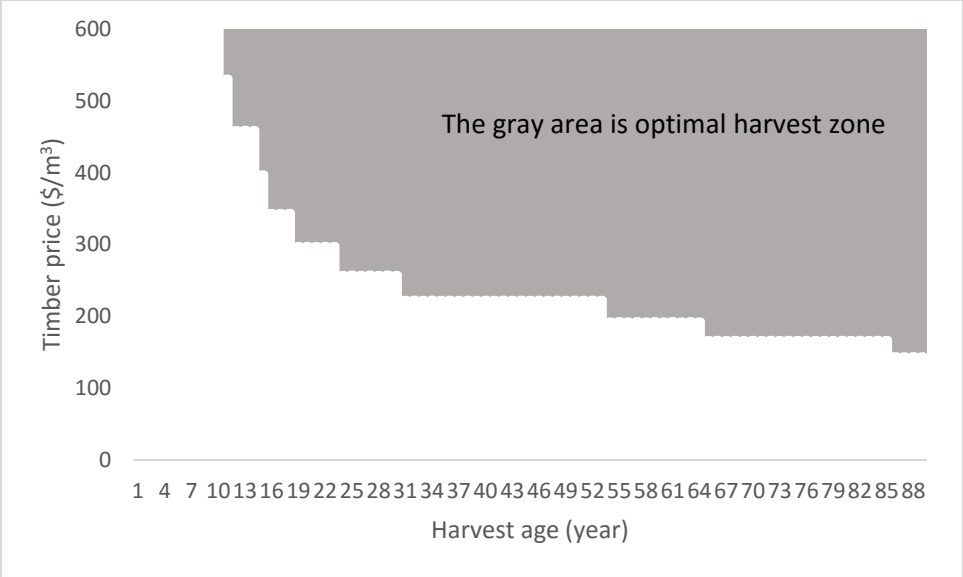


Figure 16 Sawtimber price threshold for the case of carbon-forest under SPB risk

Figure 17 and Table 14 present the comparing timber price threshold changes among timber only case, carbon plus timber case, and carbon plus timber under SPB for all possible ages of the forest. It is apparent from this figure and table that harvest price threshold decrease as trees age for all three cases. The timber price threshold is the highest in the carbon plus timber case and the lowest in the timber only case. If the age of trees is younger than 10 years, the optimal decision is not to harvest in all cases. The carbon plus timer case require highest timber price threshold at the same given forest ages. This is because carbon store ability of forest incurs a higher opportunity cost of harvesting the forest, therefore, to offset the burden of harvest, a higher timber price (revenue) would be required compare to timber only case. The SPB damage reduces the advantage of standing forest but the damaged forest still generates higher value than

timber only case because dead trees provide carbon sequestration. The benefit from carbon sequestration of standing tree partially compensates the lost from reducing total volume of harvest by SPB damage.

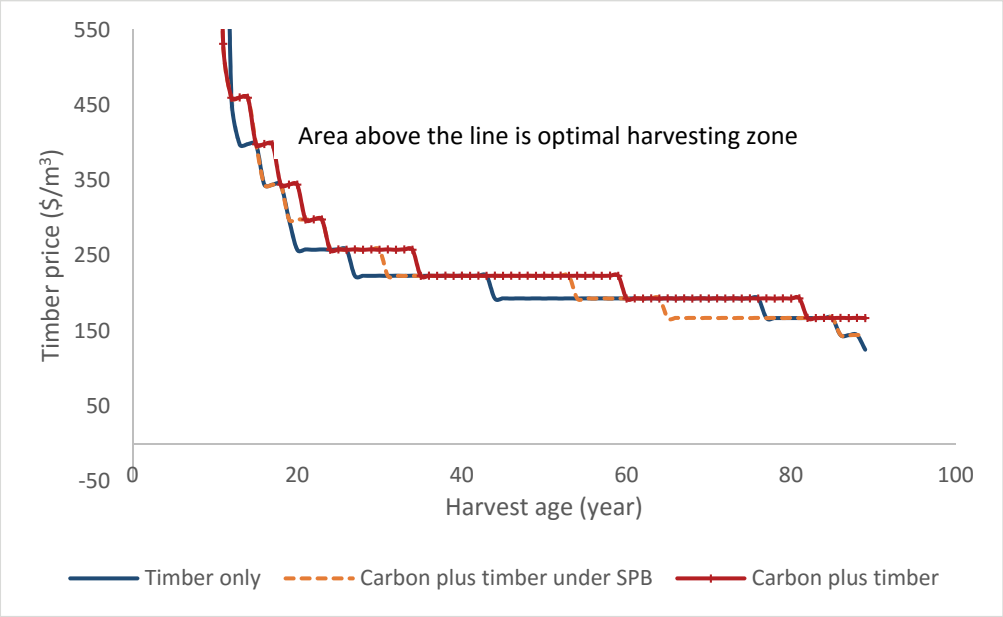


Figure 17 Comparisons of price threshold changes (timber only vs carbon forest under SPB vs carbon forest)

Table 14 Comparison of timber price threshold ages

Age	Timber only	Carbon Forest	Carbon forest under SPB risk
10	Not harvest	1000	1000
11	460	531	531
20	258	344	297
40	223	258	227
60	193	223	193
80	167	223	167
86	144	167	144
89	125	167	144

4.4.2 Sensitive analysis for carbon social cost

Figure 18 presents infinite rotation valuation for fixed harvest under various levels of social cost of carbon. As the social cost of carbon increases from $50/t to $75/t, the expected NPV of the forest increases from $4224/ha to $5164/ha at 2.4% discount rate. The optimal rotation age does not change; as the social cost of carbon increases, the value of the forest increases.

The bareland price changes for flexible harvest (real option) of infinite ration under various levels of social cost of carbon are shown in Figure 19. The bareland price changes for fixed harvest under various levels of social cost of carbon are shown in Figure 18. If the carbon social cost is $50/t, the bareland value converges to $6699/ha, after eight cycle of harvest-and-replant. If the carbon social cost is $75/t, the bareland value converges to $7408/ha, after eight cycle of harvest and replant. If the carbon social cost is $90/t, the bareland value converges to $7841/ha, after eight cycle of harvest-and-replant. Compare to fixed harvest case, flexibility adds approximately 59% to the value of bareland under a $50/t social cost, 54% under a $75/t social cost, 51% under a $90/t social cost.

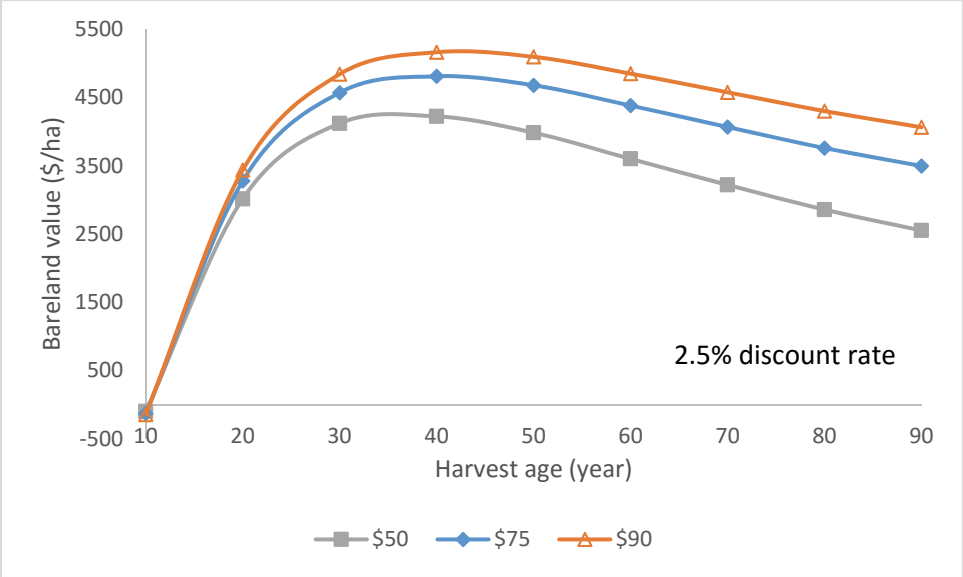


Figure 18 Market value of bareland under various levels of social cost of carbon

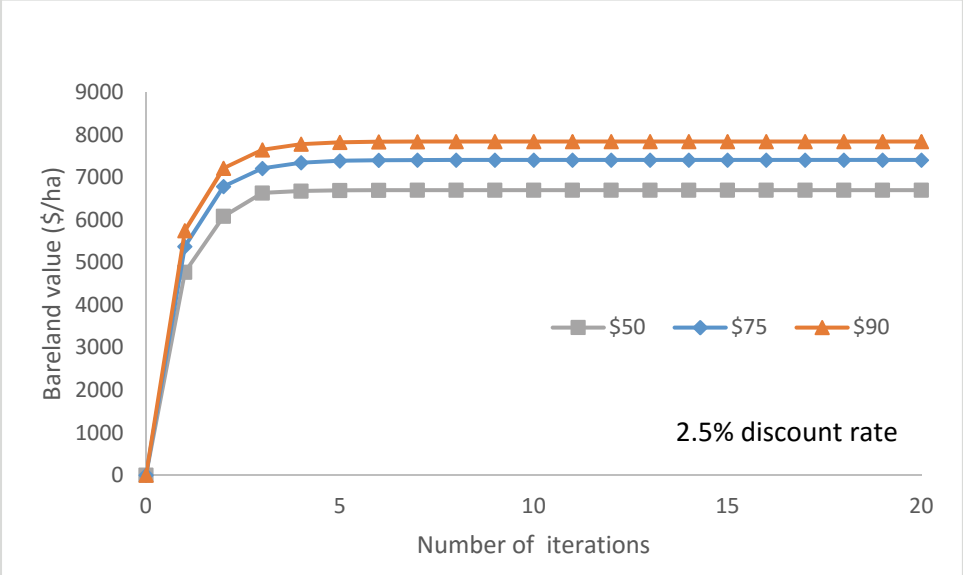


Figure 19 Market value of bareland change under various social costs of carbon

The timber price threshold changes for all possible ages of the forest under various level of social cost of carbon are presented in Figure 20. If the timber price is above the dotted line, the forest owner's best decision is to harvest. On the other hand, if the timber price is below the threshold at a given age, the optimal decision is to postpone harvest until the threshold price is reached for the respective age. The harvest price threshold decreases as the social cost of carbon decreases. There is no significant difference between harvest threshold prices if the age of the forest is young (less than 20 years old). If the forest age is 36 years, the timber price threshold is \$257/m^3 for a \$90/t of carbon social cost, \$223/m^3 for a \$50/t of carbon social cost, and \$223/m^3 for a \$75/t of carbon cost, respectively. The timber price threshold decreases as the trees grow. The higher social cost of carbon increases the opportunity cost to harvest trees. Therefore, it requires a higher timber price is necessary to compensate the loss of the opportunity cost associated with cutting trees down. Therefore, as the carbon social cost increases, the forest owner would consider delay timber harvest if anything else remains the same.

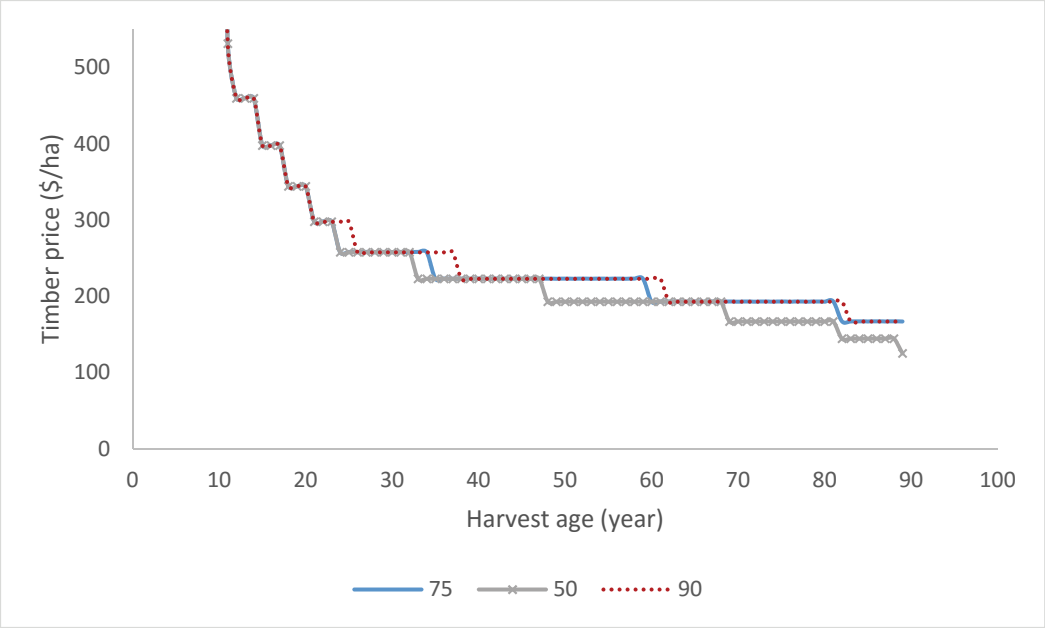


Figure 20 Timber price threshold by different social costs of carbon

4.4.3 Sensitivity analysis for SPB risk

Fixed harvest valuation (infinite rotation) under various SPB damage rates are illustrated in Figure 21. If the SPB damage rate increases, the value of bareland would decrease. If 1% of the forest is damaged by SPB, the forest value is $4308/ha at the optimal rotation age (40 years old). However, if 2% of the forest is damaged by SPB, the forest value is $3681/ha at the optimal harvest age (30 years old). If 3% of the forest is damaged by SPB, the forest value is $2908/ha at the optimal harvest age (30 years old). As the SPB risk increases, both the bareland value and the optimal rotation age decrease because high SPB infestation reduces both total harvest volume and carbon sequestration ability of trees. This generates a potential profit loss to the forest owners by reducing timber productivity in forest. When forest owners make a harvest decision, they need to

determine if the rate of return from continuing the investment in the forest is worth more than the rate of return received from an alternative investment (Jacobson 2015). Therefore, incentives from continuing to grow the trees would decrease under high SPB infestation risk by decreasing the future expected rate of return from continuing the investment in the trees. Thus, forest owner's choice is seeking other opportunities to invest, for example, stock markets, mutual funds, or other alternatives instead of deferring harvest.

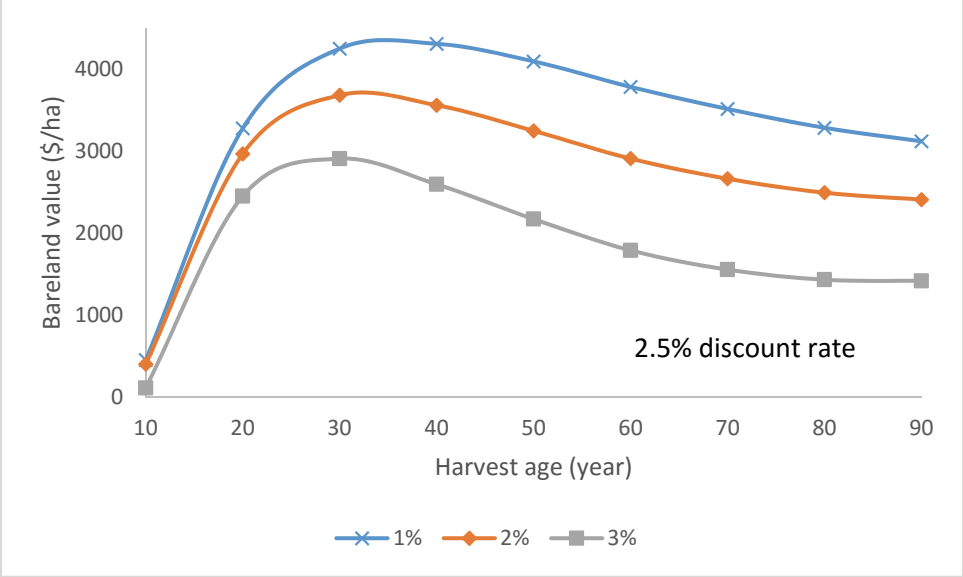


Figure 21 Value of bareland (fixed harvest) at various SPB risks

The change of real option value (flexible harvest valuation) under various SPB damage rates are shown in Figure 22. The real option values decrease from $6918/ha to $5169/ha as SPB risk rises from 1% to 3%.

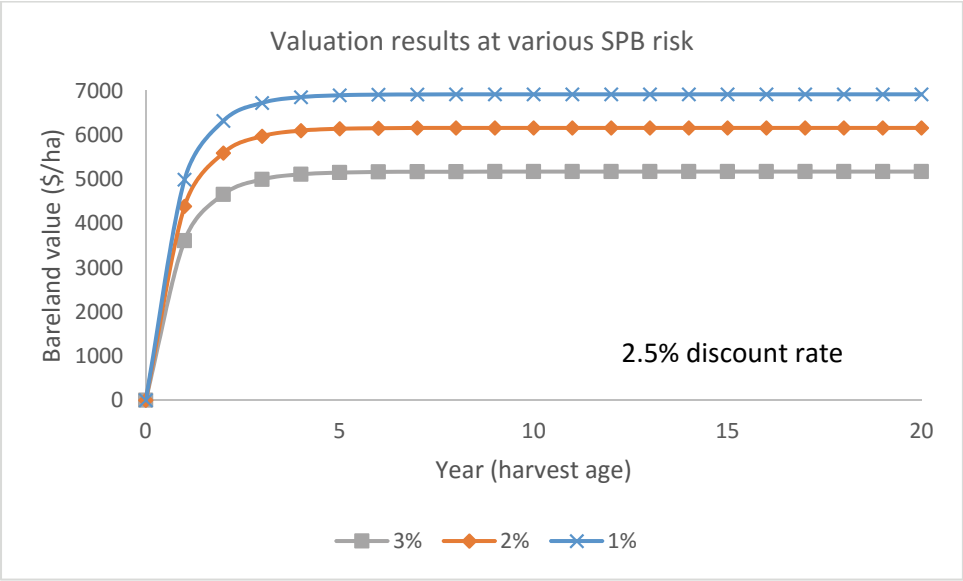


Figure 22 Market value of bareland (flexible harvest) changes at various SPB risks

The timber price threshold for harvesting at various SPB damage rates. For example, the harvest price threshold is \$297/m^3 at a 1% SPB risk, \$258/m^3 at both 2% and 3% SPB risk at age 23 is shown in Figure 23. If the forest age is 40 years, the price threshold is \$223/m^3 at 1% and 2% SPB risk, \$193/m^3 for the case of 3% SPB risk. A higher SPB risk reduces the benefit from keeping the forest. Therefore, harvesting is optimal at a lower timber price as SPB damage risk becomes more severe, especially, if the forest is younger than 55 years.

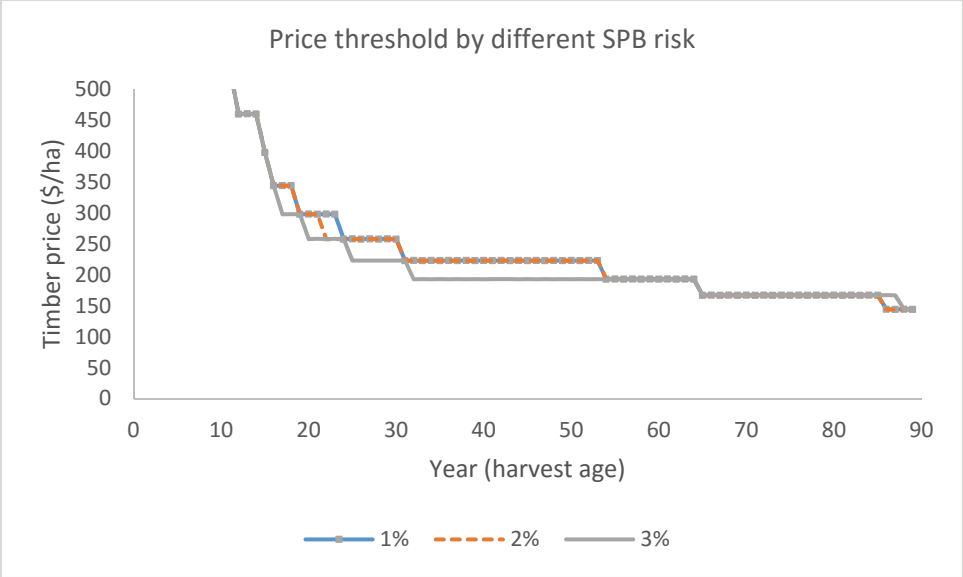


Figure 23 Optimal harvest price flow at various SPB damage rates

4.5 Conclusion

This essay enhances our understanding of the combined impact of the three factors including timber price volatility, forest carbon sequestration ability, and the impact of SPB damage on forest manager's decision making. The optimal harvest thresholds provide useful guideline for forest owners by offering an insightful decision making tool which can be compared with actual timber price in every year. The major finding of this essay is that several uncertainties including saw timber price volatility, climate change and insect outbreaks would influence forest value and that the flexible harvest decision making using real options is a better strategy than the fixed harvest decision. A higher bareland value is generated if a flexible harvest decision making (real option) by

incorporating stochastic price movement is allowed because the value of flexibility adds to forest values when flexible harvest decision is allowed.

The CO_2 sequestration ability of a forest enhances the bareland value while SPB outbreaks reduce the bareland value. However, if we consider the carbon sequestration ability of damaged trees, the bareland value is still higher than that without considering carbon storage of damaged trees. The value of standing trees is higher as the carbon social cost increases due to increasing opportunity cost of carbon sequestration on trees.

As the global CO_2 concentration increases under climate change, the value of carbon storage of forest would increase. Therefore, at higher social cost of carbon, higher timber price is required to warrant harvesting. Moreover, the high social cost of carbon also adds value to wood products because the wood products also contribute to carbon storage. Frank Werner (2005) analyzed GHG impact of a use of wood products in Switzerland. They found that the material substitute effect of wood products offsets CO_2 emissions by 0.6 Mt of avoided CO_2 emissions per year in Switzerland. Higher SPB risk tends to reduce the bareland value of forest. The higher bareland value of carbon forest provides an incentive to forest owner to plant new forests and perform intensive treatments to keep forests healthy and productive. When social cost of carbon is high, the incentive from converting abandoned agricultural land to forest land and using wood products instead of other material would become higher. U.S. forests currently absorb 10% of national GHG emissions (Ingerson 2009). Increasing forest rotation age by increasing value of standing trees could enhance forests CO_2 storage by deferring harvest. This might provide positive impacts on CO_2 mitigation in the southern U.S. This

study confirms that standing forests could provide social benefit by absorbing CO_2. However, planting new forests and keeping them healthy may require additional cost such as cost of pesticide and fertilization. This might carry an extra burden to forest owners. Therefore, policy makers should establish legislation that provide additional incentives to forest owners to offset extra burden by differing harvest and planting new forest. Emissions trading may be one of the solutions. Under emissions trading, the forest owners could earn carbon credit by standing forest and sell them in domestic and international market. The carbon trading has been employed in some countries. For example, in New Zealand, the government passed the New Zealand Emission Trading Scheme (NZETS) in 2008. Under the NZETS, the post-1989 forests (planted on and after 1st January 1990) are qualified as carbon credit that could be accumulated or immediately sold in carbon market (Tee et al. 2014). This could provide extra income to forest owners and the extra cash flow might generate incentives to forest owner to harvest new forests.

A limitation of this study is the absence of considering various different forest management schemes including pruning, thinning and fertilizing. Also, the pesticide control impact should be considered for the case of SPB outbreak risk in future research. The impact of CO_2 fertilizations on forest productivity might be included in real option valuation equations as well. As shown in the second essay, section 4, increasing CO_2 at the atmosphere would enhance forest productivity and thus provide extra profit to forest owners. The increments of timber products may offset the loss from timber damages by

SPB infestation under climate change. To consider these factors, more sophisticated real option valuation modeling approaches will be necessary in the further studies.

5. OVERALL SUMMARY AND CONCLUSIONS

The purpose of this study is to assess the impact of climate changes on U.S. forests including different aspects of changes in southern pine beetle (SPB) outbreak patterns, forest productivity and the forest owner's decision under various uncertainties. The impact of climate change on the risk of SPB infestation and the cyclical pattern of the outbreaks using generalized linear models (GLM) and spectral analysis is evaluated in the first essay. One major finding of this essay is that there is a positive relationship between SPB outbreak and unsalvaged volume of trees killed by SPB, average spring temperature, minimum winter temperature, maximum spring temperature a year ago and maximum winter temperature while the negative relationship is detected between SPB outbreak and spring precipitation, winter precipitation a year ago, and average fall temperature in the current year. The second major finding indicates that the risk of SPB outbreaks would not respond to climate change in one direction, but in general, short- and mid-term (2012–2060 and 2031–2060) future risk would be larger than the long-term (2061–2098) future risk for all climate scenarios while the magnitude of damages vary across the southern U.S. Under the projected global climate change, SPB outbreaks tend to occur more frequently, from 6–7 years to 2–5 years. The conclusions are: 1) the southern U.S. forests would be exposed to SPB risk at a higher probability in the short- and mid-term future (2012–2060, 2031–2060) than in the long-term future (2061–2098); 2) SPB outbreak in the region responding to climate change will occur with a higher

frequency; and 3) the magnitude of infestations would vary temporally and spatially without a significant hike point.

The second essay investigates the effects of CO_2 fertilization and climate variables on forest productivity across the U.S. using panel data analysis and future climates projected by GCMs. The estimated panel data models indicate that there is a significant correlation between climate variables and forest productivity. Generally, forest productivity increases as temperature increases, precipitation decreases in both quadratic and linear estimation models. Also, biomass, CO_2 concentration in the atmosphere, soil moisture and soil water storage availability have a positive correlation with forest productivity. The projection results suggest that global climate change, in general, would enhance future forest productivity in several U.S. regions including the South, the Costal Pacific, the northern Great Plains, the North, the central Intermountain, and the southern Great Basin although forest productivity in the southern Great Plains will be likely threatened by global climate change. The findings suggest that appropriate mitigation and adaptation strategies to climate change will be necessary, especially for the southern Great Plains of the U.S.

The real options valuation approach to management decision making of U.S. southern loblolly pine forests considering uncertainties including timber price volatility, forest carbon sequestration ability, and impacts of SPB damage on forest value is demonstrated in the third essay. The results show that forest owners can face a mixed outcome of these uncertainties when they make forest management decision, and the real option approach helps the forest managers consider future consequence through allowing

the flexible harvest decision. Generally, a higher bareland value is generated if a flexible harvest decision making (real option) is allowed compared to a fixed harvest. The standing forest has CO_2 sequestration ability and this ability could generate extra value in the forest while SPB outbreaks reduce the bareland value. The extra carbon value increases as the carbon social cost increase. Therefore, as climate change becomes more looming due to CO_2 concentration in the atmosphere, the value of standing forests would increase due to enhanced opportunity cost of carbon sequestration ability of forests. Continuous efforts of pest management for forests are necessary since a higher SPB risk tends to reduce the bareland value of forests. Also, employing marketable climate policy such as emissions trading is necessary to create a market carbon price and offset extra cost to keep forest.

The general finding is that predicted climate change will likely affect U.S. forests via various pathways. It might alter forest disturbances, forest productivity, and forest land value. Climate change, however, will have a mixed impact on U.S. forests and different impacts across regions, which calls for region-specific adaptation and mitigation strategies. Continued monitoring would be necessary for the regions expected to hot and dry condition in the future. These regions might experience severe SPB outbreaks and the SPB infestation could accelerate continuous decline of forest productivity as climate change progresses. A decrease in forest productivity due to SPB outbreaks and climate change translates into profit loss to regional forest owners.

This study can be enhanced in several areas. For the first essay, finer resolution data would help establish a greater accuracy on SPB studies. The interaction terms between

seasonal climate and precipitation variables could expand our knowledge of understanding about relationships among the variables in the empirical model. Applying time varying coefficient modeling to estimation and projection strategies allows us to examine more long term impacts of climate change on SPB infestation risk and provide more realistic projection results. For the second essay, further studies regarding the role of external variables including wildfire, insect outbreaks, and human activity on forest productivity would be worthwhile. Including interaction terms or applying time varying coefficients would allow us to obtain more realistic estimation and projection results. In the third essay, including various forest management schemes such as thinning and fertilization in real option model would enhance the model accuracy. In addition, evaluating forest owner's cash flow incorporating CO_2 fertilization impact on forest productivity and damage from SPB risk could be a valuable research topic.

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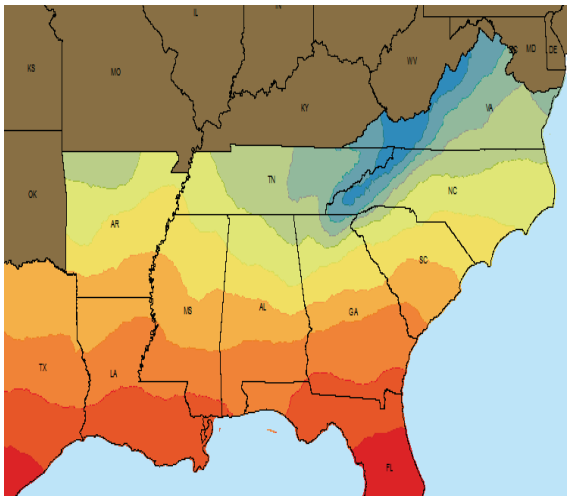
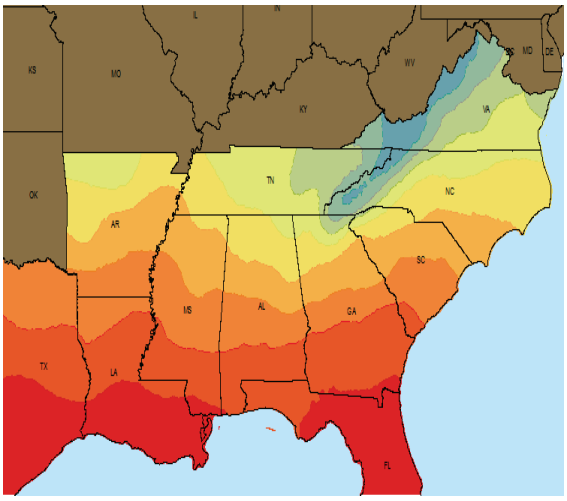
APPENDIX

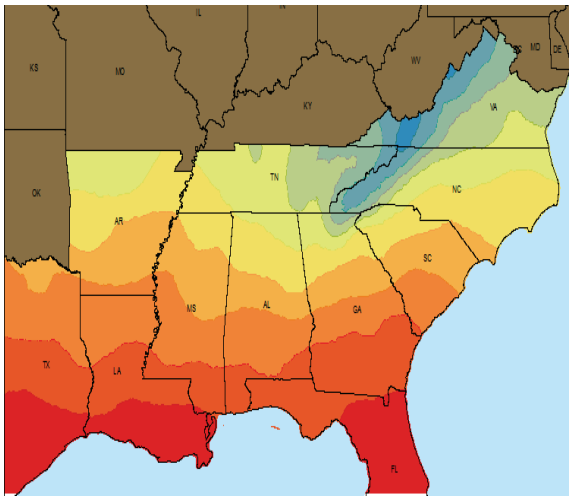
(a) Spring temperature in year 2010



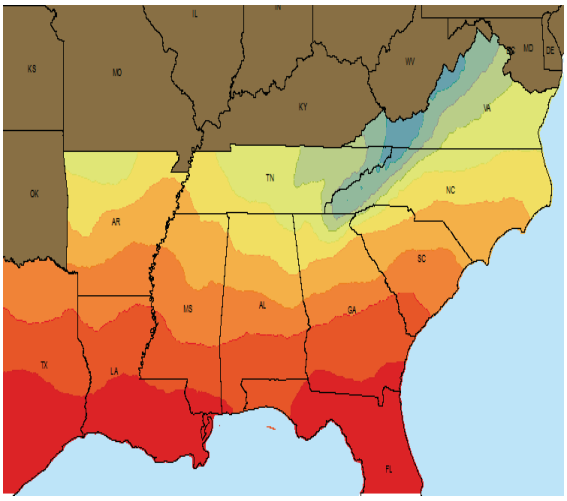
(b) Spring temperature from RCP4.5



(c) Spring temperature from RCP 6.0



(d) Spring temperature from RCP 8.5



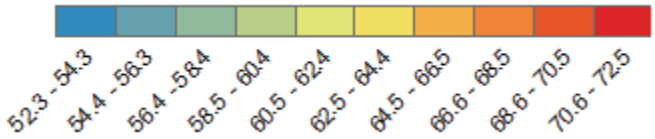
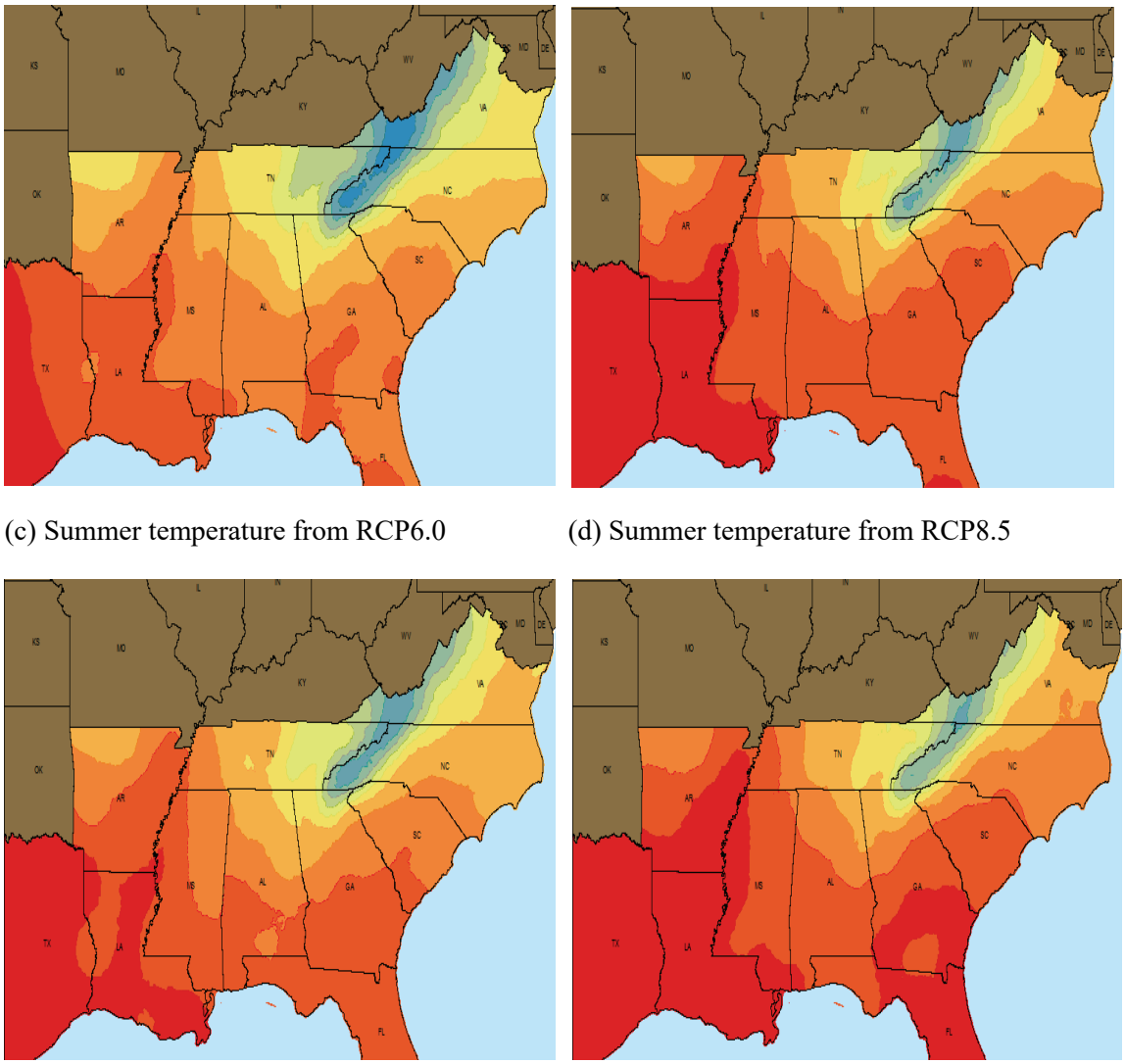


Figure A1 Projected average monthly spring temperature from GCMs under different scenarios for 2020-2060, °F

(a) Summer temperature in year 2010

(b) Summer temperature from RCP4.5



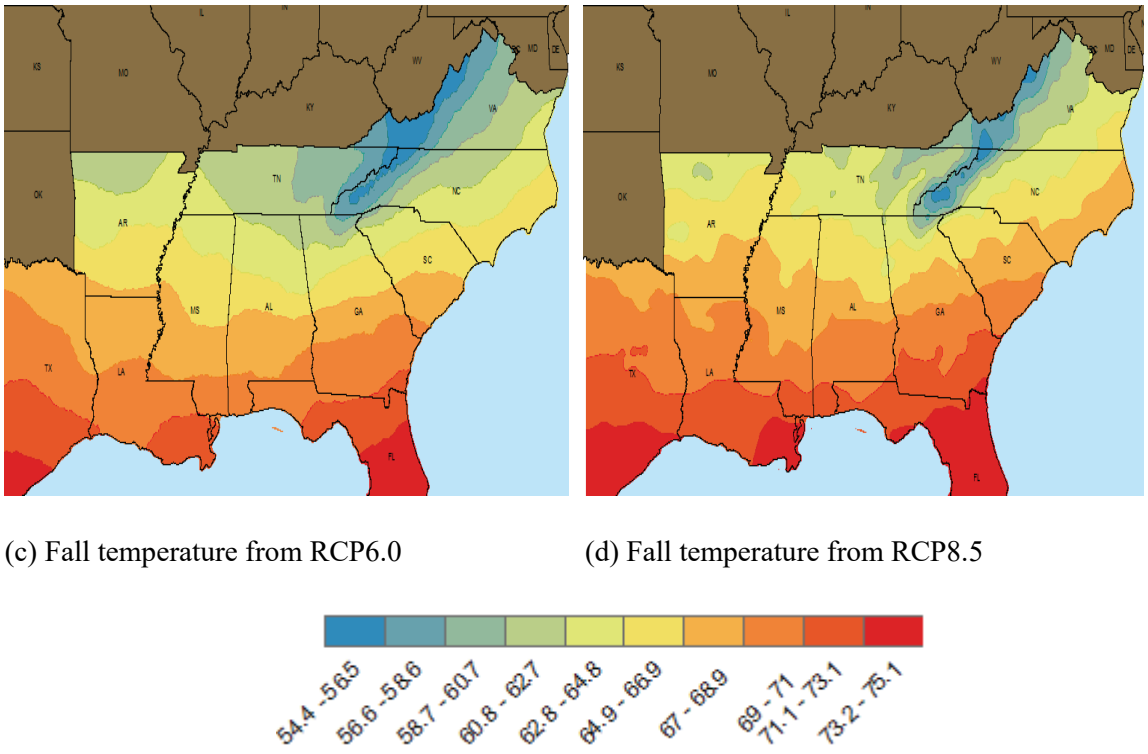
(c) Summer temperature from RCP6.0

(d) Summer temperature from RCP8.5

Figure A2 Projected average monthly summer temperature from GCMs under different scenarios for 2020-2060, °F

(a) Fall temperature in year 2010

(b) Fall temperature from RCP4.5

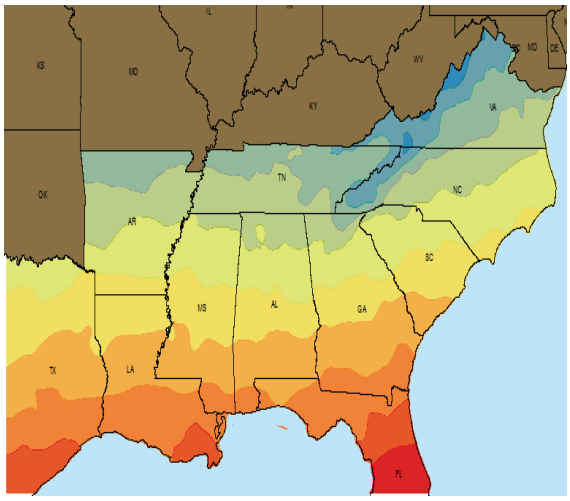


(c) Fall temperature from RCP6.0

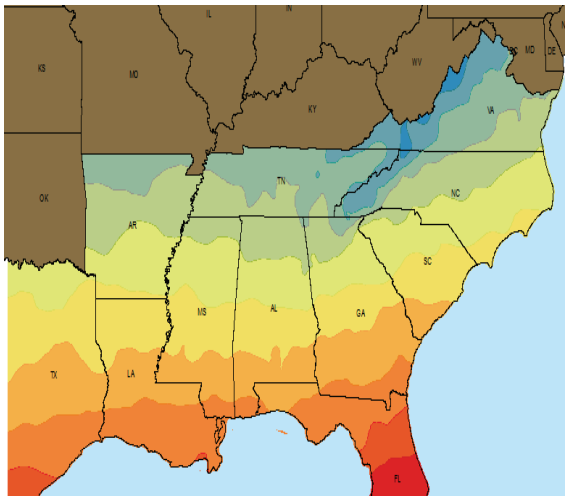
(d) Fall temperature from RCP8.5

Figure A3 Projected average monthly fall temperature from GCMs under different scenarios for 2020-2060, °F

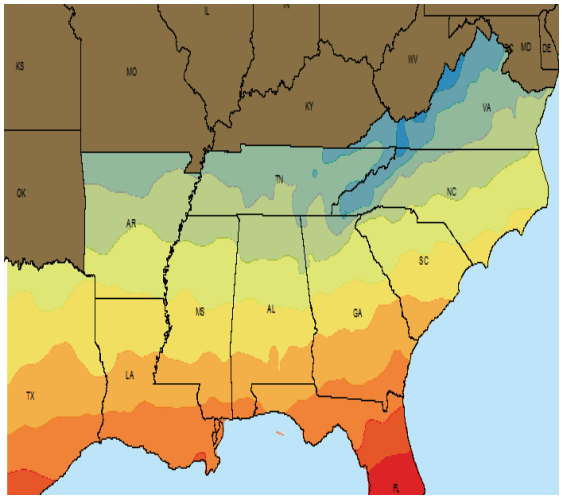
(a) Winter temperature in year 2010



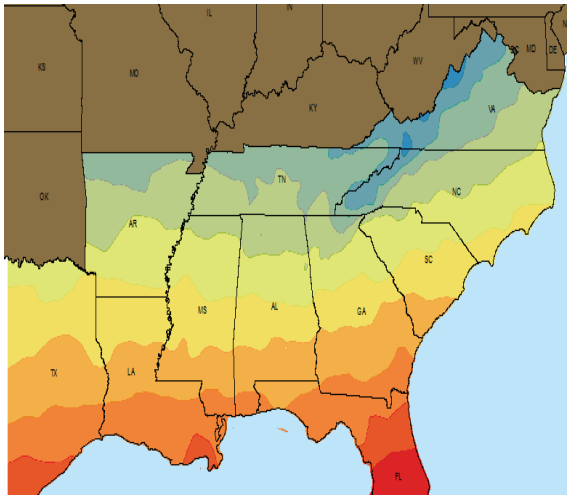
(b) Winter temperature from RCP4.5



(c) Winter temperature from RCP6.0



(d) Winter temperature from RCP8.5



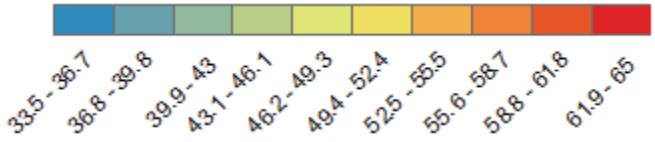
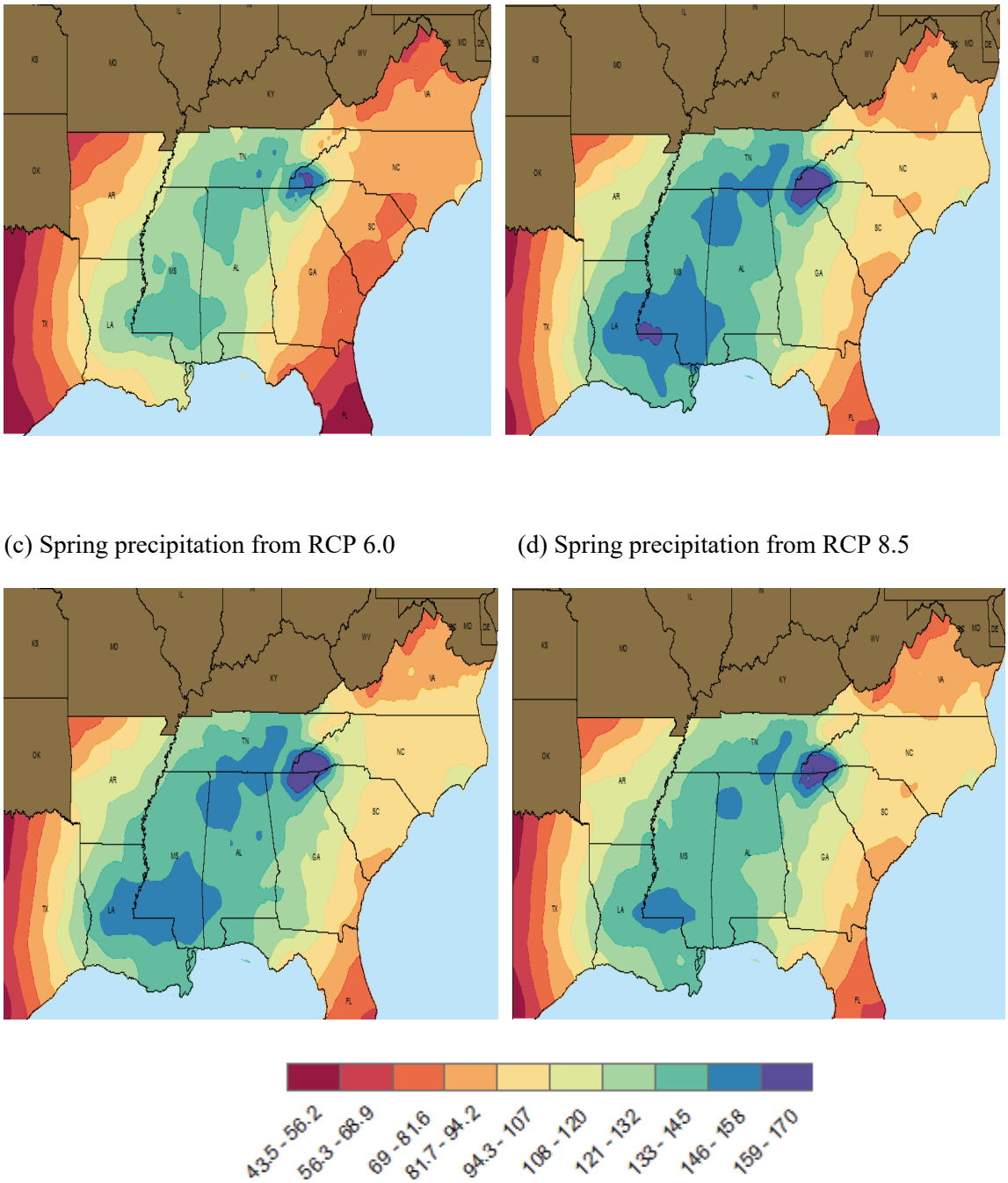


Figure A4 Projected average monthly winter temperature from GCMs under different scenarios for 2020-2060, °F

(a) Spring precipitation in year 2010

(b) Spring precipitation from RCP4.5



(c) Spring precipitation from RCP 6.0

(d) Spring precipitation from RCP 8.5

Figure A5 Projected average monthly winter precipitation from GCMs under different scenarios for 2020-2060, mm

Table A1 Average marginal effect of SPB risk (full model)

Variable description	Independent variable	Average marginal effect	Delta-Method S.E	*P*-value
Unsalvaged volume in current year	USV	0.0456	0.0127	0.0000
Spring temperature	SPT	0.0118	0.0051	0.0200
Summer temperature	SMT	-0.0138	0.0085	0.8710
Fall temperature	FLT	-0.0141	0.0058	0.0500
Winter temperature	WNT	-0.0504	0.0028	0.0750
Minimum spring temperature	MinSpring	-0.0249	0.0023	0.2890
Minimum summer temperature	MinSummer	0.0015	0.0039	0.7060
Minimum fall temperature	MinFall	0.0037	0.0214	0.1510
Minimum winter temperature	MinWinter	0.0035	0.0015	0.0160
Maximum spring temperature	MaxSpring	0.0007	0.0029	0.8020
Maximum summer temperature	MaxSummer	0.0027	0.0060	0.6460
Maximum fall temperature	MaxFall	-0.0002	0.0026	0.9420
Maximum winter temperature	MaxWinter	-0.0010	0.0022	0.6380
Spring temperature one year ago	SPT1	0.0040	0.0053	0.7500
Summer temperature one year ago	SMT1	-0.0243	0.0092	0.0080
Fall temperature one year ago	FLT1	-0.0130	0.0061	0.0330
Winter precipitation one year ago	WNT1	-0.0006	0.0002	0.0100
Min spring temperature one year ago	MinSpring1	0.0024	0.0054	0.6560
Min summer temperature one year ago	MinSummer1	0.0007	0.0041	0.8730
Min fall temperature one year ago	MinFall1	0.0036	0.0019	0.0560
Min winter temperature one year ago	MinWinter1	0.0042	0.0014	0.0040
Max spring temperature one year ago	MaxSpring1	-0.0023	0.0030	0.4370
Max summer temperature one year ago	MaxSummer1	0.0079	0.0075	0.2960
Max fall temperature one year ago	MaxFall1	0.0016	0.0026	0.5280
Max winter temperature one year ago	MaxWinter1	0.0036	0.0014	0.0080
Spring temperature two year ago	SPT2	-0.0027	0.0038	0.4730
Summer temperature two year ago	SMT2	0.0226	0.0097	0.1670
Fall temperature two year ago	FLT2	-0.0034	0.0047	0.4780
Winter temperature two year ago	WNT2	-0.0066	0.0023	0.5210
Min spring temperature two year ago	MinSpring2	-0.0035	0.0022	0.1200
Min summer temperature two year ago	MinSummer2	-0.0085	0.0040	0.0710
Min fall temperature two year ago	MinFall2	-0.0009	0.0023	0.7020
Min winter temperature two year ago	MinWinter2	0.0029	0.0015	0.0580
Max spring temperature two years ago	MaxSpring2	0.0088	0.0033	0.0070
Max suumer temperature two years ago	MaxSummer2	-0.0080	0.0061	0.1920
Max fall temperature two years ago	MaxFall2	0.0031	0.0030	0.3100

Max winter temperature two years ago	MaxWinter2	-0.0028	0.0023	0.2260
Spring precipitation	SPP	0.0002	0.0003	0.4280
Summer precipitation	SMP	-0.0001	0.0003	0.7770
Fall precipitation	FLP	-0.0007	0.0003	0.0300
Winter precipitation	WNP	0.0001	0.0002	0.8110
Spring precipitation one year ago	SPP1	-0.0004	0.0003	0.1470
Summer precipitation one year ago	SMP1	-0.0007	0.0003	0.0140
Fall precipitation one year ago	FLP1	-0.0003	0.0003	0.3780
Winter precipitation one year ago	WNP1	-0.0004	0.0002	0.0780
Spring precipitation two year ago	SPP2	0.0004	0.0003	0.1840
Summer precipitation two year ago	SMP2	-0.0003	0.0003	0.2060
Fall precipitation two year ago	FLP2	-0.0005	0.0003	0.1270
Winter precipitation two year ago	WNP2	0.0001	0.0003	0.6810
Unsalvaged volume one year ago	USV1	0.0040	0.0105	0.7070
Unsalvaged volume two year ago	USV2	0.0143	0.0097	0.1390
State Dummy1	d1	0.0033	0.0015	0.0250
State Dummy2	d2	0.0015	0.0012	0.1880
State Dummy3	d3	0.0061	0.0025	0.0150
State Dummy4	d4	0.0028	0.0015	0.0640
State Dummy5	d5	0.0033	0.0022	0.1380
State Dummy6	d6	0.0029	0.0016	0.0620
State Dummy7	d7	0.0022	0.0009	0.0100
State Dummy8	d8	0.0030	0.0014	0.0290
State Dummy9	d9	0.0004	0.0007	0.5180
State Dummy10	d10	0.0021	0.0016	0.1850
Catastrophic Dummy	ci	0.0020	0.0002	0.0000

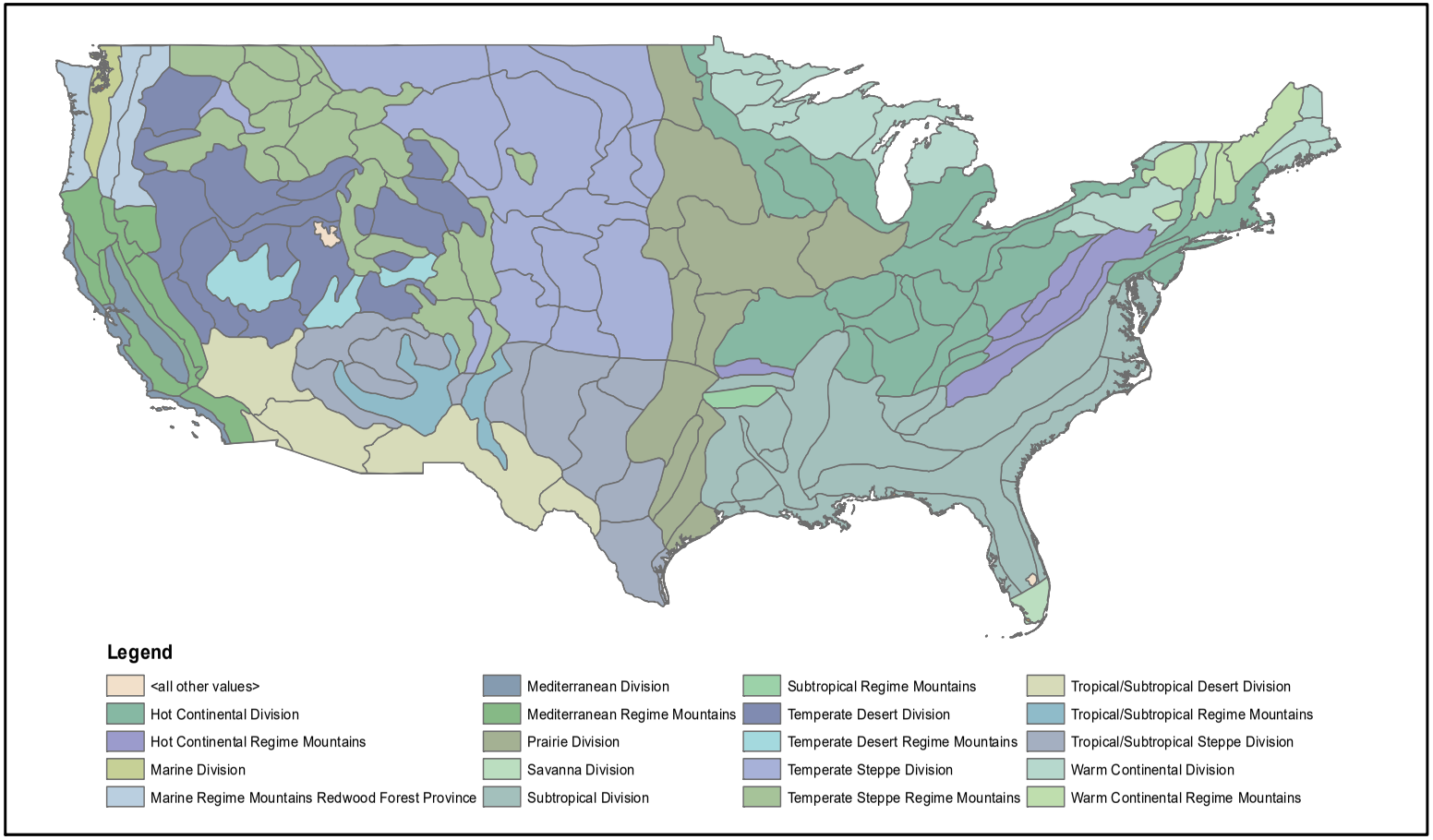


Figure A6 Major eco-climatic domains in U.S. (Source: Data from Rudis (1999))

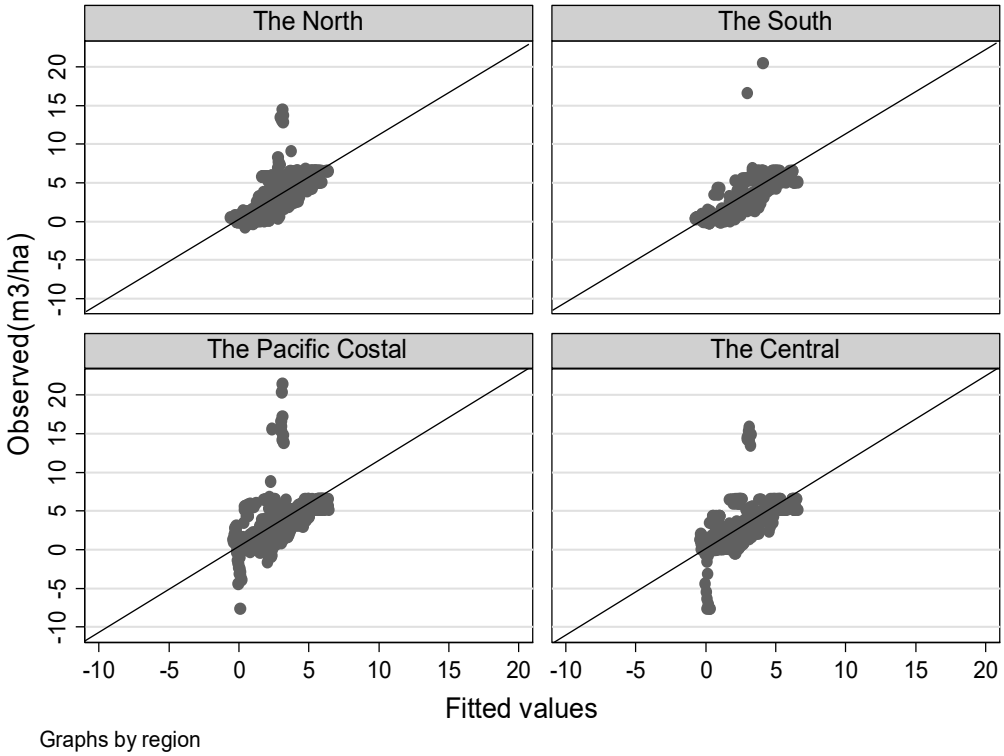


Figure A7 Fitted vs observed plot by region (quadratic estimation, by region)

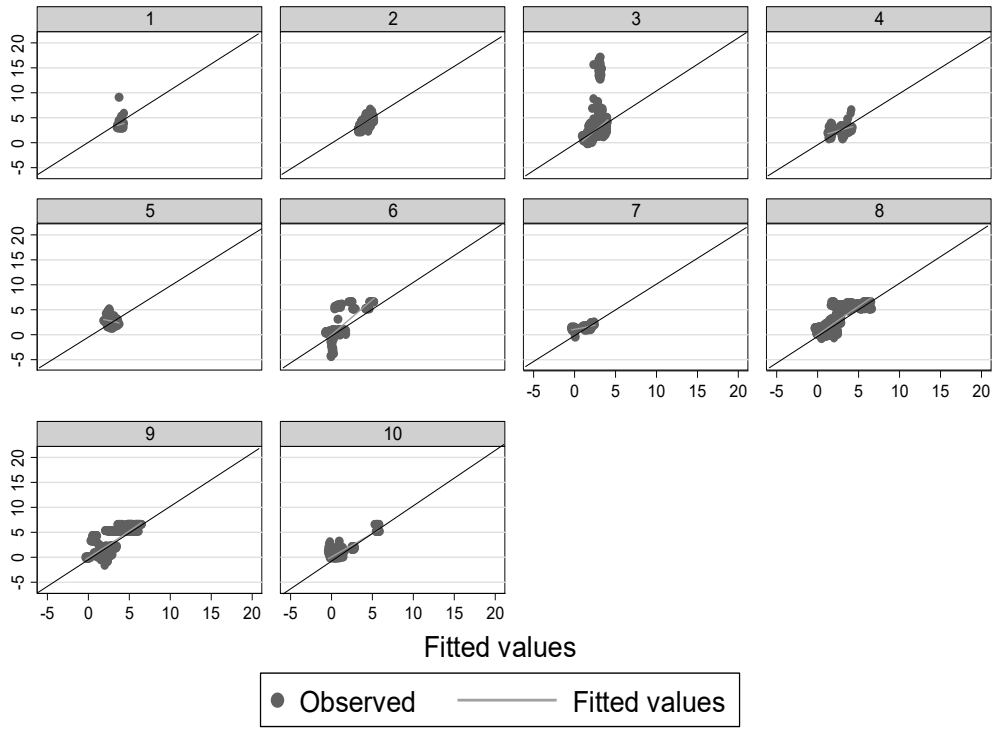


Figure A8 Fitted vs. observed plot (quadratic estimation, by forest type)

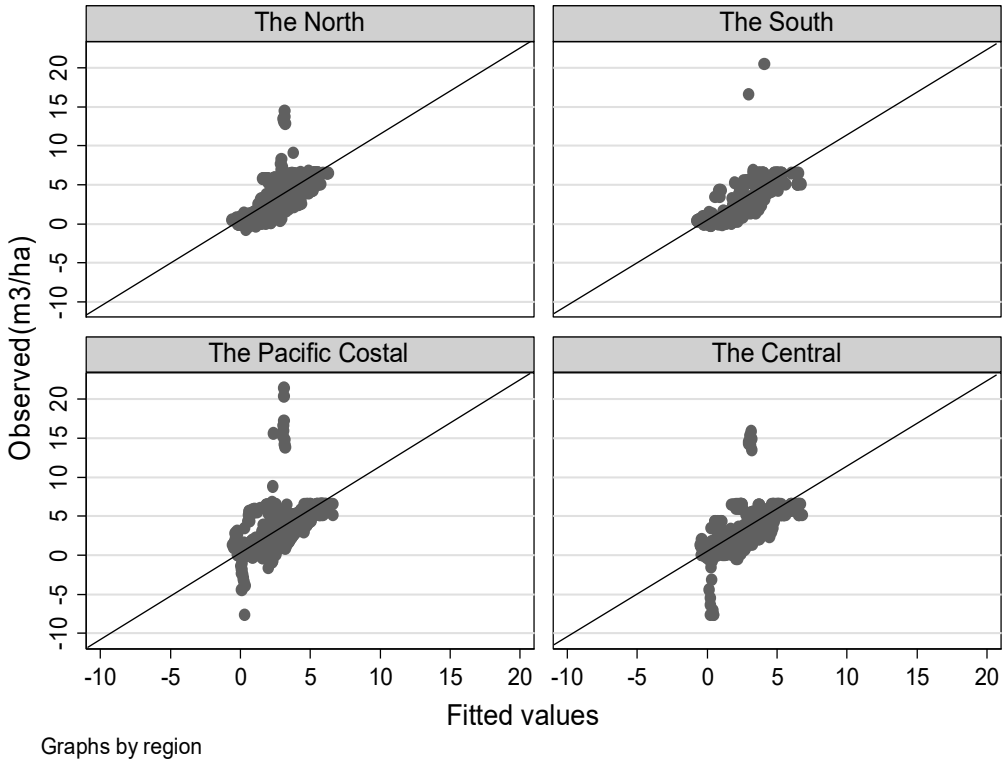


Figure A9 Fitted vs. observed plot by region (stepwise estimation, by region)

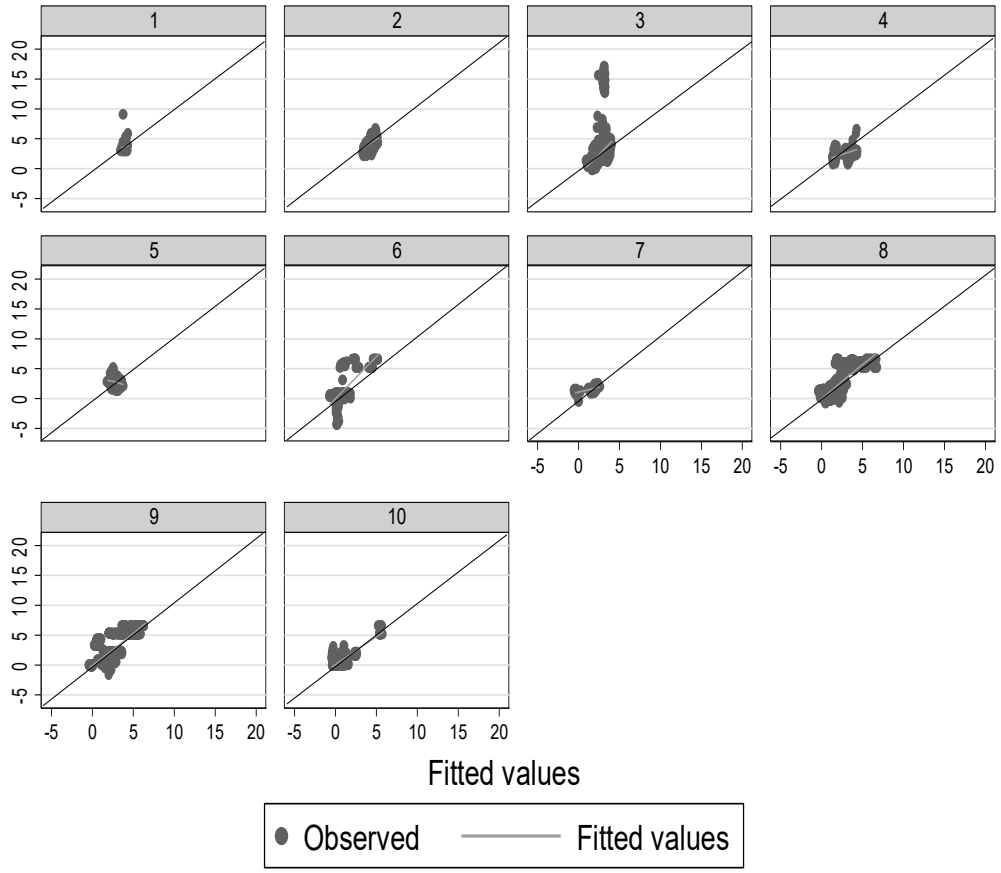


Figure A10 Fitted vs. observed plot (stepwise estimation, by forest type)

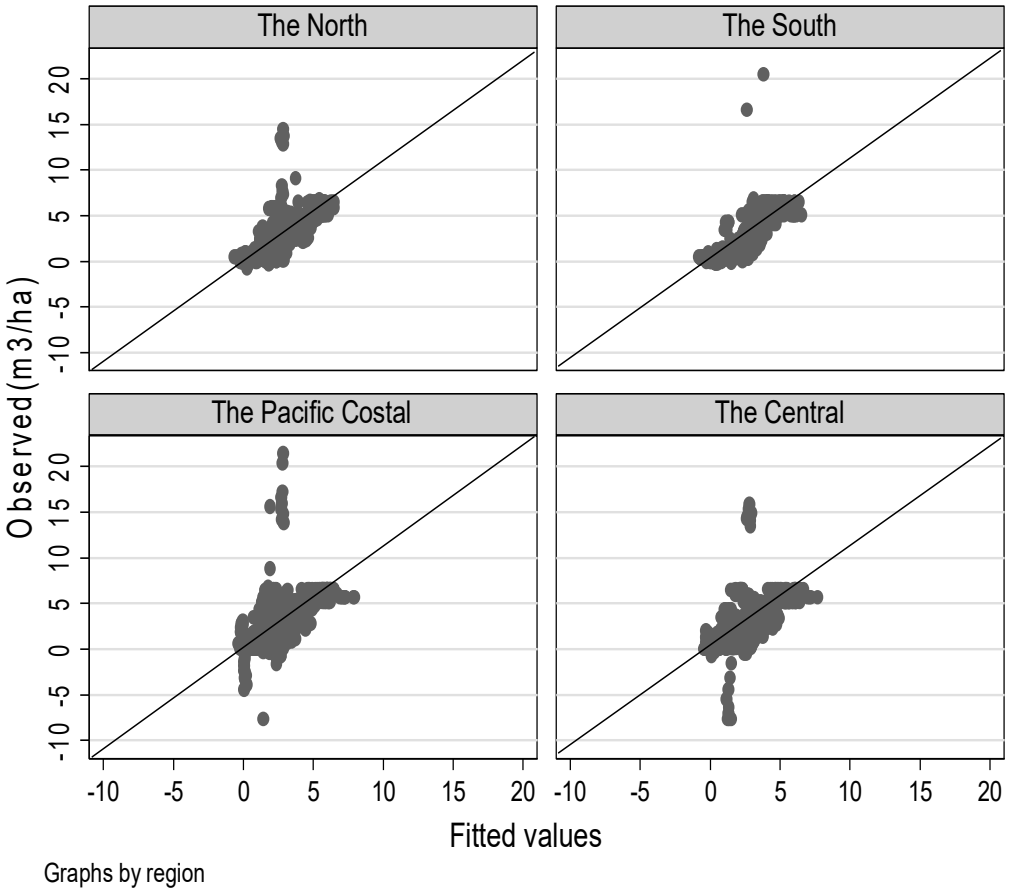


Figure A11 Fitted vs. observed plot by region (linear estimation, by region)

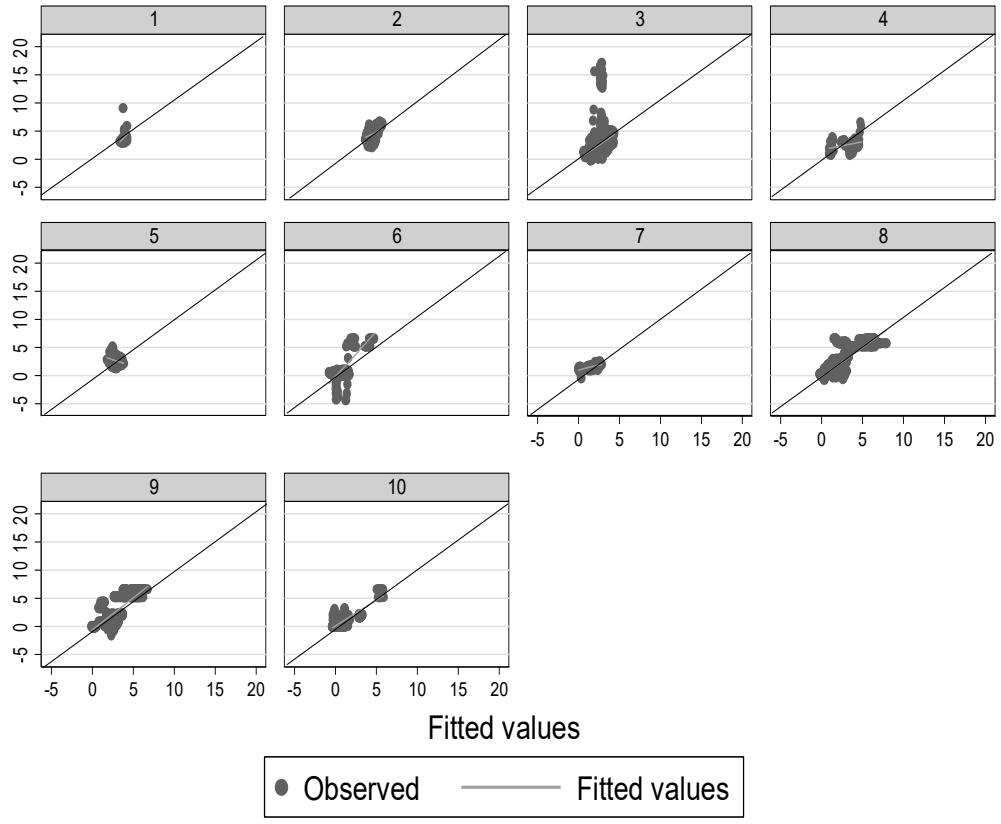


Figure A12 Fitted vs. observed plot (linear estimation, by forest type)

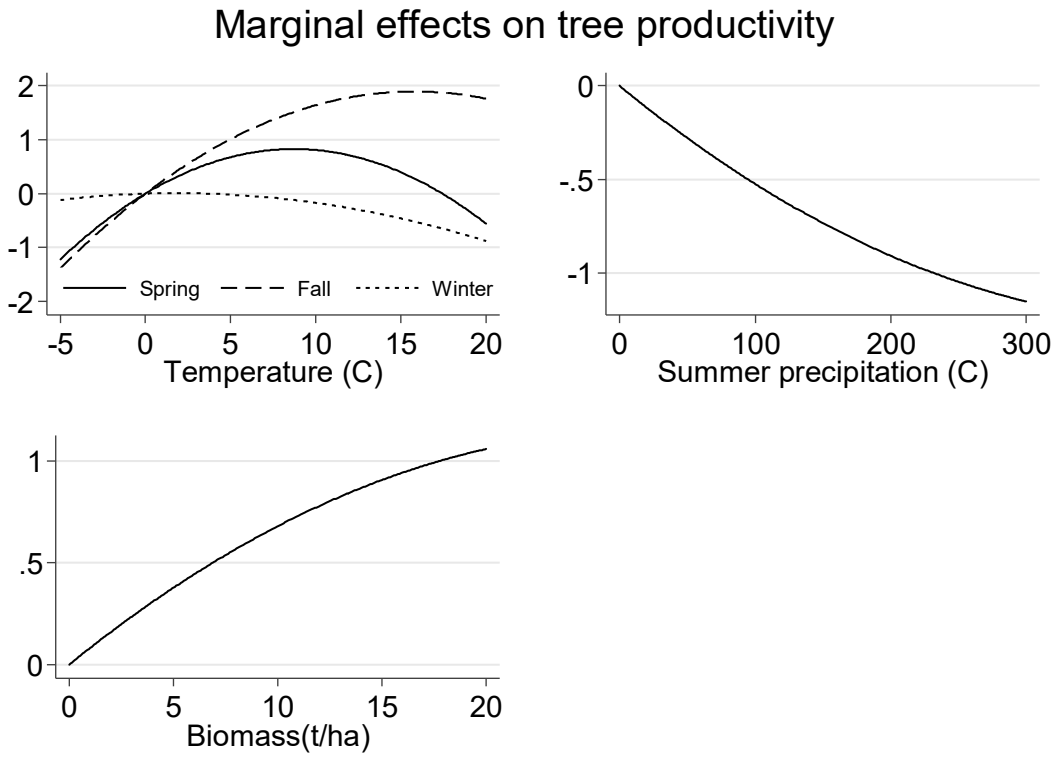


Figure A13 Marginal effects of temperature (fall, spring, winter), precipitation (summer), and biomass on forest productivity

Table A2 Variables in essay 2.

Variables	Variable description	Values for Estimation	Data Source
Average annual net growth	"Average annual net growth of growing-stock trees (at least 5 inches d.b.h.), in cubic feet. Average annual net cubic-foot growth of growing-stock trees on timberland".	Convert Average annual net growth(cf) into (m^3) then divide by timberland area(ha)	Forest Inventory Data Online [4]
Biomass[5]	"Above and belowground carbon in live trees (at least 1 inch d.b.h./d.r.c), in short tons. Carbon in the belowground portion of the tree. The carbon (pounds) of coarse roots > 0.1 inch in root diameter. Calculated for live trees with a diameter >=1 inch, and dead trees with a diameter >=5 inches, for both timber and woodland species". Tree A woody plant usually having one or more erect perennial stems, a stem diameter at breast height of at least 3.0 inches, a more or less definitely formed crown of foliage, and a height of at least 15 feet at maturity. "	Above and below ground carbon/ area(ha). The carbon above and below ground value are calculated by "Above and below ground biomass"*0.6. Therefore above and below ground carbon can be measurement of above and below ground biomass	Forest Inventory Data Online
Density	Area: area of timberland, in acres (acre) Tree count: Number of growing-stock trees (at least 5 inches d.b.h.)	Tree count /Timber land area(ha)	Forest Inventory Data Online
CO_2 concentration in atmosphere	The increasing amount of CO2 in the atmosphere in global level		Earth system research laboratory, NOAA[6]

[4] The forest variables are available at Forest Inventory Data Online (FIDO) (USDA Forest Service 2015).
[5] Above and below ground Biomass × 0.6 = Above and below ground Carbon
[6] CO2 concentration data is available at Tans and Keeling (2014).